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Green Hub-and-Spoke Network Design for Aviation Industry

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Abstract

In response to the rapid growth of environmental problems related to air transportation including emissions and noise, aviation authorities and industries have implemented stricter environmental regulations and targets in the early 2000s to encourage airlines to become greener. Different emission mitigation measures to achieve these targets have been developed. This study introduces a new mitigation measure. In addition to minimizing total cost of flow and establishing hubs, the measure aims at minimizing the greenhouse gas emissions, fuel consumption and noise in the design of airline hub-and-spoke network. We develop a multi-objective mixed integer-programming model and use several methodologies to determine the best design.

Our computational results are based on the CAB data set for the domestic US aviation sector. For assessing the value of the new mitigation measure, we develop cumulative marginal abatement cost curves for reducing the projected annual CO_2 emissions from 2020 to 2050 for the domestic US air transportation. Our results indicate that using the new measure can cost-effectively decrease the projected cumulative (2020-2050) CO_2 emissions by more than 250 and 200 million tonnes relative to the classical model, which relies on minimizing the total cost of flow and opening hubs only. We conclude that the new measure not only provides a practical solution for the airlines facing high fuel cost, emission trading schemes or carbon tax systems but it can also play an important role in achieving sustainable and environmental-friendly targets.

Keywords:

Green aviation, Emission mitigation measure, Hub-and-spoke network, Multi-objective model, Marginal abatement cost

1. Introduction

Aviation experts believe that environmental concerns and regulations constitute an important impediment to the future growth of the air transport industry (de Neufville and Odoni, 2003). The environmental impacts of aviation, especially noise and greenhouse gas emission, have become growingly important since the past half-century (Mahashabde et al., 2011).

Noise is the most readily sensed environmental impact of aviation activity. It has been an important cause for complaints, resulting in vigorous public resistance against most airport expansion schemes (Waitz et al., 2004). In 2017, over 4 million people in Europe were exposed to noise over 55 decibel due to aviation (European Environment Agency (EEA), 2017).

Greenhouse gas emissions from aviation are growing considerably with an increase of 3.6% per annum at the global level (Schäfer et al., 2016). If the current trend retains, aviation emission levels in 2036 will be 155%-300% higher than in 2006 (ICAO, 2013) and carbon dioxide (CO_2) emissions from international aviation are estimated to almost quadruple by 2050 compared to 2010 (European Commission, 2017). Greenhouse gas emissions from aviation pose serious risks to public health. These risks are witnessed through the increasing number of heart diseases, neurotic and respiration disorders, cancers, and eventually early deaths. Due to these health related issues, the level of greenhouse gas emissions has led to serious concerns among the public (US Environmental Protection Agency (EPA), 2000, 2008a, 2008b, 2010; Luo and Mooney, 1999).

In addition to the emission problem, the aviation industry is also facing energy problems and increasing fuel cost (Krile et al., 2015). According to the reports of International Air Transportation Association (IATA), the fuel expense for airline industry in 2018 is roughly \$180 billion, 20.5% higher than what it was in 2017 (IATA, 2018).

The environmental and cost problems of the aviation industry are expected to become even more substantial since aviation has the highest growth rate among all modes of transport with an average annual growth rate of 4.5-5% (Agarwal, 2012; Boeing, 2009). In response to this growth, governments, aviation authorities, and industries have implemented strict environmental regulations and targets to encourage airlines to become greener (Marchettini et al. 2014). Airlines and aviation industries, adopted a set of ambitious targets to achieve their vision of carbon-emission-free aviation. Some of these targets are 1) a 1.5% fuel efficiency

improvement per year from 2009 until 2020, 2) a carbon-neutral growth starting in 2020, and 3) a 50% reduction in overall CO_2 emissions by 2050, relative to the level in 2005 (IATA, 2013). In order to achieve these targets, multiple emission mitigation measures are developed. These measures can be grouped into five categories: technological measures, sustainable alternative fuels, air traffic management, airline operational strategies, and positive economic measures (Schäfer et al., 2016). Refer to Fig. 1 for more details.

{Please insert Fig. 1 here.}

Despite the inherent multi-objective nature of hub-and-spoke networks in real life, only a few studies consider multiple objectives. Costa et al. (2008) propose a bi-objective optimization model by minimizing the total cost of flow and opening hubs and time to process the flows entering the hubs. Alumur and Kara (2009), Alumur, Kara and Karasan (2009, 2012) and Alumur, Yaman and Kara (2012) study the hub location problems based on real life hub networks by jointly minimizing travel times and transportation costs. Amin-Naseri et al. (2018) study an uncapacitated single allocation p-Hub median problem by minimizing the maximum uncertainty and the total transportation cost in the network.

Due to emphasis on reducing the environmental problems caused by aviation, the literature on green aviation has grown rapidly. Multiple authors developed models to minimize the noise annoyance and fuel consumption (Frair, 1984; Visser and Wijnen, 2001, 2003). However, using only environmental criteria as objective functions can lead to infeasible solutions from an economical point of view. Single objective mathematical programming models create the dilemma of choosing between economic (based on cost or profit objectives) or environmentally friendly (based on environmental objectives) solutions for policy makers. On the other hand, multi-objective optimization models can deal with this drawback by including objectives for profit and environment simultaneously. Khoo and Teoh (2014) develop a bi-objective programming model for green fleet planning considering green performance and profit as objective functions for airlines. Rosskopf et al. (2014) study balancing of economic and environmental goals in long-term airline fleet planning using a multi-objective linear programming model. Müller et al. (2018) propose a mixed-integer linear programming model to study fleet planning decisions under different emission targets. Prats et al. (2011) develop a multi-objective optimization methodology for the design of noise abatement procedures in combination with take-offs trajectory optimization algorithms. Ho-Huu et al. (2018) present a new multi-objective optimization formulation for the design and allocation of optimal aircraft departure trajectories by minimizing the number of people

1 annoyed, fuel consumption and the frequency of aircraft noise events. Our study contributes
2 to this stream of literature.

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4 In this paper, we introduce a new mitigation measure. Similar to the classical hub-and-
5 spoke network design studies, our measure aims at minimizing the total cost of flow and
6 opening hubs. Different from these studies, it aims at minimizing the greenhouse gas
7 emissions, fuel consumption and noise. We develop a multi-objective mixed integer-
8 programming model and address the following research questions:
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- 11 1. How do the green objectives influence the hub-and-spoke network design and
12 fleet composition?
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- 14 2. How much potential does the new measure possess?
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- 16 3. Is the new measure cost-effective? If so, how much can the new measure cost-
17 effectively reduce the emissions?
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22 Our model is based on the classical formulation of hub location problem presented in
23 Ebery et al. (2000). This formulation minimizes the total cost of flow and establishing hubs.
24 Different from this classical formulation, we study objective functions on different
25 greenhouse gas emissions, fuel consumption and noise pollution. Another fundamental
26 difference is that we consider the fleet composition. Hence, our model optimizes the location
27 of hub airports and allocation of non-hub to hubs airports as well as the aircraft fleet
28 composition and their allocation in the network by considering of both economic and
29 environmental objectives.
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36 We rely on international reference methods for measuring noise, air pollution and fuel
37 consumption. Our new objective functions aim at minimizing the noise level, the total
38 greenhouse gas emissions and the total fuel consumption. The new multi-objective
39 mathematical model optimizes the total cost of flow and establishing hubs as well as the
40 environmental objectives simultaneously to design environmentally friendly hub-and-spoke
41 network. We use multiple different Multi-Objective Decision-Making (MODM) methods
42 including the ε -constraint, weighted sum, weighted min-max, and goal-programming
43 methods in combination with grouping Analytic Hierarchy Process (AHP) approach to arrive
44 at the ideal solution.
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53 Our contribution is twofold: First, we introduce a new mitigation measure based on
54 multi-objective mathematical modeling for airlines hub-and-spoke networks, where we
55 consider fleet composition and objective functions on the total cost of flow and opening hubs,
56 different greenhouse gas emissions, fuel use, and noise level. The model optimizes the air
57 transportation hub-and-spoke network structure (location of hub airports and allocation of
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non-hub airports to hubs) as well as the use of the aircraft fleet of airlines and their allocation in the network by taking into consideration environmental and economic criteria simultaneously. To the best of our knowledge, available literature has not addressed this measure up to now although airlines and aviation authorities are confronted with it in practice. Second, we evaluate the role and contribution of the new measure for achieving aviation sustainability targets. For this purpose, we develop cumulative marginal abatement cost (MAC) curves for reducing the projected cumulative CO_2 emissions from 2020 to 2050 for the domestic US aviation. The results indicate that the new measure can cost-effectively reduce 8-10% of cumulative CO_2 emissions in this period relative to the classical model of the hub location problem.

The remainder of the paper is organized as follows. A review of relevant literature is summarized in Section 2. The new multi-objective model is developed in Section 3. In Section 4, we present the data used in the numerical experiments and the solver used for the optimization. We introduce the alternative methods for solving the optimization problem in Section 5. The results of the numerical experiments for the domestic US air transportation network are reported in Section 6. Section 7 provides an assessment of the new emissions mitigation measure. In Section 8, we present our conclusions and ideas for further research.

2. Literature Review

There are three main research streams related to the subject of this paper: 1) hub location problems, 2) optimization models for green aviation, and 3) economic assessment of emission mitigation measures. This section reviews the literature on these three streams.

2.1. Hub Location Problems

The literature on hub location problems is quite rich. Before 2000, hub location literature focused on defining and formulating fundamental models with a single objective. Different classical hub location problems such as p-hub median, hub covering, and p-hub center were broadly studied in the hub location literature (See Campbell et al. (2002) and Alumur and Kara (2008) for reviews). Alumur and Kara (2008), Campbell and O’Kelly (2012) and Contreras (2015) emphasize that it is necessary to go beyond the classical models and define new models to better match with the real life aspects of the hub location problems. Given this requirement, Gao and Qin (2016) consider stochastic travel times and Akgün and Tansel (2018) study non-complete networks between hub nodes based on real-world road and rail networks. Ghaffarinasab et al. (2018) deal with the competitive single and multiple allocation

1 hub location problems. Rothenbächer et al. (2016) propose a real-world integrated hub
2 location problem and tactical service network design for combined road-rail freight
3 transportation. Rostami et al. (2018) tackle the problem of hub reallocation, when disasters
4 hit the originally defined hubs.
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7 As discussed in Section 1, there exist multiple studies multiple criteria in the context of
8 hub location problems (Costa et al., 2008; Alumur and Kara, 2009; Alumur, Kara and
9 Karasan, 2009, 2012; and Alumur, Yaman and Kara, 2012; Amin-Naseri et al., 2018).
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12 Even though there are studies that aim at formulating the real life aspects of the hub
13 location problems, the rapid growth rate of the aviation sector results in more problems
14 around fuel consumption, harmful emissions, nonstop noise near airports, and community
15 complaints about the effects on their quality of life and health (National Aeronautics and
16 Space Administration (NASA), 2010). Our study differs from and contributes to the hub
17 location literature by developing a hub location model with multiple economic and
18 environmental objectives.
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25 **2.2. Optimization Models for Green Aviation**

26 In this sub section, optimization models to tackle the environmental aviation problems
27 are discussed.
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30 Fleet planning optimizes the composition of the fleet of an airline. Khoo and Teoh
31 (2014), Roskopf et al. (2014), and Müller et al. (2018) develop fleet planning optimization
32 models by considering not only an economic objective but also environmental objectives.
33 Khoo and Teoh (2014) propose the Green Fleet Index to quantify how green the fleet of an
34 airline is. The authors formulate a bi-objective stochastic dynamic programming model to
35 obtain the optimal number/type of aircrafts that are needed to realize an optimal profit and
36 required green performance. Roskopf et al. (2014) present a bi-objective model to
37 determine the optimal fleet composition, which balances the airline's asset value and the NO_x
38 emissions from flight operations. Müller et al. (2018) study the effect of retrofits and
39 emission thresholds on airline fleet planning. They conclude that retrofits and emission
40 thresholds could make a considerable contribution to achieve short-term emission targets.
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52 Several studies investigate the design of departure and arrival trajectories with less fuel
53 consumption, emission, and noise. Visser and Wijnen (2001, 2003) develop an optimization
54 tool to create environmentally optimal departure and arrival trajectories. Visser (2005) extend
55 the multi-objective optimization capability of the tool by investigating a variety of
56 environmental criteria that are generic in nature as well as site-specific. Zachary et al. (2010)
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develop a non-linear integer-programming model to obtain the optimal combination of departure and arrival trajectories, operational procedures and fleet composition by minimizing noise and pollutant emissions. Prats et al. (2011) develop a multi-objective lexicographic optimization for the design of noise abatement procedures in combination with trajectory optimization algorithms for take-offs. Similarly, Hartjes and Visser (2016) and Zhang et al. (2016) develop a genetic optimization algorithm to derive environmentally friendly aircraft departure trajectories focusing on local NO_x emissions, noise abatement, and fuel use. Ho-Huu et al. (2017) employ a multi-objective evolutionary algorithm based on decomposition to design optimal departure routes by minimizing noise and fuel consumption. In a related study, Kim et al. (2014) develop a mixed integer-programming model to schedule the departure and arrival operations on the runways by minimizing total emissions produced on the airport surface and in the terminal area. Ho-Huu et al. (2018) propose a model for design of aircraft departure trajectories with objectives of minimizing the fuel consumption level, noise level and number of annoyed people.

2.3. Economic Assessment of Emission Mitigation Measures

The economic feasibility of emission mitigation measures is investigated by multiple studies (Holland et al., 2011; Morris et al., 2009; Raper et al., 2009). Jesse et al. (2012) provide cost-benefit analysis of retrofit programs and Schäfer et al. (2015) propose a techno-economic analysis of CO_2 emission mitigation measures. Our study also contributes to this stream of literature.

3. Mathematical model

In this section, we present our multi-objective mixed-integer linear programming (MILP) model. An overview of the indexes, parameters, decision variables, and dependent variables in this model is given in Appendix A.

3.1. Problem statement

We consider a complete graph $G=(N,A)$, where $N=\{1,\dots,n\}$ is the set of nodes and $A=N\times N$ is the set of directed arcs. We use W_{ij} to indicate the flow of passengers from node i to node j , and d_{ij} denotes the Euclidian distance between nodes i and j . These distances satisfy the triangle inequality. Each origin-destination path has potentially three components: collection (from the origin to a hub), transfer (between one or more hubs), and distribution

(from the last hub to the destination). Hub-and-spoke networks use fewer arcs and concentrate flows on these arcs to realize transportation economies of scale. The transport cost per unit flow for each component is proportional to the Euclidian distance between the nodes involved and is multiplied by a component-specific factor. These factors are χ , α and δ for the collection, transfer and distribution components, respectively.

The number of hubs is not given but it is a decision variable. A fixed cost of F_k is incurred for establishing a hub at node k . Each node can receive from and send flows to more than one hub (multiple allocations).

Two types of aircrafts, heavy and large, are distinguished (de Neufville and Odoni, 2003). We define $V = \{v_1, v_2, \dots, v_{|V|}\}$ as the set of heavy aircraft types flying in the transfer component and $V' = \{v'_1, v'_1, \dots, v'_{|V'|}\}$ as the set of large aircraft types flying in the collection and distribution components, and $U = V \cup V'$ the set of all types of aircrafts, where $|V|$ and $|V'|$ denote the number of heavy and large types of aircraft, respectively. In addition, c^u denotes the cost of using one aircraft of type $u \in U$ per unit distance.

3.2. Assumptions

Similar to the hub location problems in the literature, we make the following four assumptions (Campbell and O'Kelly, 2012, Contreras, 2015):

1. Flows have to be routed via the hub node(s). A consequence of this assumption is that direct connections between origin-destination non-hub nodes are not permitted. Hence, origin-destination paths in the hub-and-spoke network must contain at least one hub node.
2. Due to the inter-hub transfer efficiencies, we have $\alpha < 1$ while $\chi = \delta = 1$. This assumption reflects economies of scale for the transfers via inter-hub connections (Alumur and Kara, 2008).
3. The distances between all nodes satisfy the triangle inequality.
4. The set-up cost for hub arcs equals zero. This permits the hub nodes to be interconnected at no extra cost. Together with Assumptions 2 and 3, this assumption leads to a complete network for the hub nodes, i.e., all hubs are fully interconnected.

3.3. Multi-Objective Model Formulation

Several formulations have been proposed for the multiple allocation hub location problem. Our model is based on the formulation presented in Ebery et al. (2000). This formulation is recognized as one of the most effective general approaches for tackling the multiple allocation hub location problem (Campbell et al., 2002).

Our objective is to determine the airline hub-and-spoke network, i.e., the location of hub airports and allocation of non-hub airports to hub airports. We also aim to optimize the aircraft fleet composition and the allocation of aircrafts within the network. We consider multiple objective functions to ensure both economic and environmental efficiency.

In what follows we provide the details of our formulation by introducing the objective functions and the corresponding constraints.

3.3.1. Cost Objective Function

Our cost objective function is inspired by the classical cost function in Ebery et al. (2000). Different from the cost function in Ebery et al. (2000), we allow for different aircraft types. Our cost function can be written as follows:

$$\sum_{i \in N} \left[\sum_{k \in N} \sum_{v' \in V'} \chi c^{v'} d_{ik} Z_{ik}^{(v')} + \sum_{k \in N} \sum_{l \in N} \sum_{v \in V} \alpha c^v d_{kl} Y_{kl}^{(i,v)} + \sum_{l \in N} \sum_{j \in N} \sum_{v' \in V'} \delta c^{v'} d_{lj} X_{lj}^{(i,v')} \right] + \sum_{k \in N} F_k H_k. \quad (1)$$

Here, $Z_{ik}^{(v')}$, $Y_{kl}^{(i,v)}$, $X_{lj}^{(i,v')}$, and H_k are decision variables. $Z_{ik}^{(v')}$ denotes the number of flights using an aircraft of type $v' \in V'$ from origin i to hub k (collection). $Y_{kl}^{(i,v)}$ is the number of flights using an aircraft of type $v \in V$ from hub k to hub l (transfer) for the flow originating at origin i . $X_{lj}^{(i,v')}$ denotes the number of flights using an aircraft of type $v' \in V'$ from hub l to destination j (distribution) for the flow originating at origin i . Finally, the binary decision variables H_k locates hubs, i.e., $H_k = 1$ when node k is a hub, and $H_k = 0$ otherwise. The total cost consists of the cost for collection, transfer, distribution and hub establishing.

3.3.2. Air Pollution and Fuel Consumption Objective Function

We use the methodology of the European Environment Agency (EEA, 2016) to estimate aircraft pollutant emissions in accordance with the previously defined decision variables for the problem. In this methodology, aircraft operations are divided into two cycles (refer to Fig. 2):

1. The Landing/Take-off (LTO) cycle includes all activities taking place near the airports at altitudes lower than 3000 feet during the departure and arrival phases of a flight.
2. The Cruise cycle includes all activities taking place at altitudes above 3000 feet during the Climb/Cruise/Descent phases of a flight.

{Please insert Fig. 2 here.}

EEA (2016) has introduced multiple methods named “Tier 1”, “Tier 2”, and “Tier 3” (divided into “Tier 3A” and “Tier 3B”), to calculate aircraft emissions. Table 1 summarizes the data/tools required for all tiers.

{Please insert Table 1 here.}

In this study, we use the Tier 3A method due to its high accuracy and data/tool requirements. According to this method, the total amount of pollutant $p \in \{VOC, NO_x, CO\}$ emitted by an aircraft of type $u \in U$ based on flight distance d_{ij} is calculated as $E_p^{(u, LTO)} + R_p^{u, C}(d_{ij})$. Here, $E_p^{(u, LTO)}$ is the amount of pollutant $p \in \{VOC, NO_x, CO\}$ emitted by an aircraft of type $u \in U$ during the LTO cycle and $R_p^{u, C}(d_{ij})$ is the amount of pollutant $p \in \{VOC, NO_x, CO\}$ emitted by an aircraft of type $u \in U$ during the cruise cycle. The total amount of pollutant $p \in \{CO_2, SO_2\}$ emitted by an aircraft of type $u \in U$ based on flight distance d_{ij} is equal to $E_p^{(u, LTO)} + R_f^{u, C}(d_{ij}) \times E_p^C$. Here, $R_f^{u, C}(d_{ij})$ is the amount of fuel burned by an aircraft of type $u \in U$ during the cruise cycle and E_p^C is amount of pollutant $p \in \{CO_2, SO_2\}$ emitted per unit fuel burned during the cruise cycle.

Then, the air pollution objective function for the VOC , NO_x and CO emissions as well as CO_2 and SO_2 emissions can be written as in Eq. (2) and Eq. (3), respectively:

$$\sum_{i \in N} \left[\sum_{k \in N} \sum_{v' \in V'} \left(E_p^{(v', LTO)} + R_p^{v', C}(d_{ik}) \right) Z_{ik}^{(v')} + \sum_{k \in N} \sum_{l \in N} \sum_{v \in V} \left(E_p^{(v, LTO)} + R_p^{v, C}(d_{kl}) \right) Y_{kl}^{(i, v)} + \sum_{l \in N} \sum_{j \in N} \sum_{v' \in V'} \left(E_p^{(v', LTO)} + R_p^{v', C}(d_{lj}) \right) X_{lj}^{(i, v')} \right] \quad \forall p \in \{VOC, NO_x, CO\}, \quad (2)$$

$$\sum_{i \in N} \left[\sum_{k \in N} \sum_{v' \in V'} \left(E_p^{(v', LTO)} + R_f^{v', C}(d_{ik}) \times E_p^C \right) Z_{ik}^{(v')} + \sum_{k \in N} \sum_{l \in N} \sum_{v \in V} \left(E_p^{(v, LTO)} + R_f^{v, C}(d_{kl}) \times E_p^C \right) Y_{kl}^{(i, v)} + \sum_{l \in N} \sum_{j \in N} \sum_{v' \in V'}^n \left(E_p^{(v', LTO)} + R_f^{v', C}(d_{lj}) \times E_p^C \right) X_{lj}^{(i, v')} \right] \quad \forall p \in \{CO_2, SO_2\}. \quad (3)$$

The objective function of fuel consumption is given by:

$$\sum_{i \in N} \left[\sum_{k \in N} \sum_{v' \in V'} \left(E_f^{(v', LTO)} + R_f^{v', C} (d_{ik}) \right) Z_{ik}^{(v')} + \sum_{k \in N} \sum_{l \in N} \sum_{v \in V} \left(E_f^{(v, LTO)} + R_f^{v, C} (d_{kl}) \right) Y_{kl}^{(i, v)} + \sum_{l \in N} \sum_{j \in N} \sum_{v' \in V'} \left(E_f^{(v', LTO)} + R_f^{v', C} (d_{lj}) \right) X_{lj}^{(i, v')} \right]. \quad (4)$$

Eq. (2) gives the total amount of VOC , NO_x , and CO emissions, whereas Eq. (3) gives the total amount of CO_2 and SO_2 emissions. Eq. (4) gives the total amount of fuel burned in the hub-and-spoke network.

3.3.3. Sound Pollution Objective Function

Aircraft noise metrics are divided into (Mahashabde et al., 2011):

1. Single-event metrics that measure the direct impact of one aircraft movement.
2. Cumulative metrics that reflect long-term exposure to aircraft noise based on all single event aircraft movements during the period considered.

Analysts commonly use the sound exposure level (SEL) as the metric to describe the noise impact of single events. According to this metric, if M movements (landings, take offs) take place during a certain period τ (expressed in seconds), the noise level ψ in A-weighted decibels is given by (Federal Interagency Committee on Noise (FICON), 1992):

$$\psi = 10 \times \log \left(\frac{1}{\tau} \sum_{j=1}^M 10^{\frac{SEL_j}{10}} \right). \quad (5)$$

SEL_j denotes the sound exposure level in A-weighted decibels related to the j th aircraft movement. For modeling noise pollution, the following variables are introduced:

$$\lambda_b^{(v, L)} = \sum_{i \in N} \sum_{l \in N} Y_{lb}^{(i, v)} \quad \forall b \in B, \forall v \in V, \quad (6)$$

$$\lambda_b^{(v', L)} = \sum_{i \in N, i \neq b} Z_{ib}^{(v')} + \sum_{i \in N} \sum_{j \in N, j \neq b} X_{jb}^{(i, v')} \quad \forall b \in B, \forall v' \in V', \quad (7)$$

$$\lambda_b^{(v, T)} = \sum_{i \in N} \sum_{l \in N} Y_{bl}^{(i, v)} \quad \forall b \in B, \forall v \in V, \quad (8)$$

$$\lambda_b^{(v', T)} = \sum_{i \in N, i \neq b} Z_{bi}^{(v')} + \sum_{i \in N} \sum_{j \in N, j \neq b} X_{bj}^{(i, v')} \quad \forall b \in B, \forall v' \in V'. \quad (9)$$

Here, B denotes the nodes exposed to noise pollution, $\lambda_b^{(u, L)}$ is the number of landings by aircrafts of type $u \in U$ at node $b \in B$, and $\lambda_b^{(u, T)}$ is the number of take offs by aircrafts of

type $u \in U$ at node $b \in B$. Using Eq. (5), the equivalent noise level at node b can be calculated as follows:

$$\psi_b = 10 \times \log \left\{ \frac{1}{\tau} \times \left[\sum_{v \in V} \lambda_b^{(v,L)} \times 10^{\frac{S_v^L}{10}} + \sum_{v \in V} \lambda_b^{(v,T)} \times 10^{\frac{S_v^T}{10}} + \sum_{v' \in V'} \lambda_b^{(v',L)} \times 10^{\frac{S_v^L}{10}} + \sum_{v' \in V'} \lambda_b^{(v',T)} \times 10^{\frac{S_v^T}{10}} \right] \right\} \quad \forall b \in B. \quad (10)$$

S_u^L and S_u^T denote the average SEL emitted by an aircraft of type $u \in U$ during landings (denoted by index L) and take offs (denoted by index T) during period τ in A-weighted decibels. In order to get an MILP model, Eq. (10) is rewritten as follows:

$$10 \times \log \left(\frac{\psi_b}{10} \right) \times \tau = \sum_{v \in V} \sum_{i \in N} \sum_{l \in N} Y_{lb}^{(i,v)} \times 10^{\frac{S_v^L}{10}} + \sum_{v \in V} \sum_{i \in N} \sum_{l \in N} Y_{bl}^{(i,v)} \times 10^{\frac{S_v^T}{10}} + \sum_{v' \in V'} \left(\sum_{i \in N, i \neq b} Z_{ib}^{(v')} + \sum_{i \in N} \sum_{j \in N, j \neq b} X_{jb}^{(i,v')} \right) \times 10^{\frac{S_v^L}{10}} + \sum_{v' \in V'} \left(\sum_{i \in N, i \neq b} Z_{bi}^{(v')} + \sum_{i \in N} \sum_{j \in N, j \neq b} X_{bj}^{(i,v')} \right) \times 10^{\frac{S_v^T}{10}} \quad \forall b \in B. \quad (11)$$

3.3.4. Constraints

Next, we formulate the aircraft availability constraints. We define n^v as the number of type $v \in V$ aircrafts required for the flights between hub nodes, i.e., for the transfer component of the network during the peak hours. Similarly, we define $n^{v'}$ as the number of type $v' \in V'$ aircrafts required for the flights between non-hub and hub nodes, i.e., for the collection and distribution components of the network during the peak hour. Based on these definitions, we have

$$n^v = \sum_{i \in N} \sum_{k \in N, l \in N, l \neq k} Y_{kl}^{(i,v)} \quad \forall v \in V, \quad (12)$$

$$n^{v'} = \sum_{i \in N} \sum_{l \in N} \sum_{j \in N, j \neq l} X_{lj}^{(i,v')} + \sum_{i \in N} \sum_{k \in N, k \neq i} Z_{ik}^{(v')} \quad \forall v' \in V'. \quad (13)$$

We further define y^u as the number of aircrafts of type $u \in U$ available for the airline during the peak hour. Then, the aircraft availability constraints can be written as

$$\sum_{i \in N} \sum_{k \in N, l \in N, l \neq k} Y_{kl}^{(i,v)} \leq y^v \quad \forall v \in V, \quad (14)$$

$$\sum_{i \in N} \sum_{l \in N} \sum_{j \in N, j \neq l} X_{lj}^{(i,v')} + \sum_{i \in N} \sum_{k \in N, k \neq i} Z_{ik}^{(v')} \leq y^{v'} \quad \forall v' \in V'. \quad (15)$$

3.3.5. The Overall Multi-Objective Model

Using the objective functions defined in Sections 3.3.1, 3.3.2 and 3.3.3 and the aircraft availability constraints formulated in Section 3.3.4, we can write our multi-objective model as follows:

$$\min \sum_{i \in N} \left[\sum_{k \in N} \sum_{v' \in V'} \chi c^{v'} d_{ik} Z_{ik}^{(v')} + \sum_{k \in N} \sum_{l \in N} \sum_{v \in V} \alpha c^v d_{kl} Y_{kl}^{(i,v)} + \sum_{l \in N} \sum_{j \in N} \sum_{v' \in V'} \delta c^{v'} d_{lj} X_{lj}^{(i,v')} \right] + \sum_{k \in N} F_k H_k \quad (1)$$

$$\min \sum_{i \in N} \left[\sum_{k \in N} \sum_{v' \in V'} \left(E_p^{(v', LTO)} + R_p^{v', C}(d_{ik}) \right) Z_{ik}^{(v')} + \sum_{k \in N} \sum_{l \in N} \sum_{v \in V} \left(E_p^{(v, LTO)} + R_p^{v, C}(d_{kl}) \right) Y_{kl}^{(i,v)} + \sum_{l \in N} \sum_{j \in N} \sum_{v' \in V'} \left(E_p^{(v', LTO)} + R_p^{v', C}(d_{lj}) \right) X_{lj}^{(i,v')} \right] \quad \forall p \in \{VOC, NO_x, CO\}, \quad (2)$$

$$\min \sum_{i \in N} \left[\sum_{k \in N} \sum_{v' \in V'} \left(E_p^{(v', LTO)} + R_f^{v', C}(d_{ik}) \times E_p^C \right) Z_{ik}^{(v')} + \sum_{k \in N} \sum_{l \in N} \sum_{v \in V} \left(E_p^{(v, LTO)} + R_f^{v, C}(d_{kl}) \times E_p^C \right) Y_{kl}^{(i,v)} + \sum_{l \in N} \sum_{j \in N} \sum_{v' \in V'} \left(E_p^{(v', LTO)} + R_f^{v', C}(d_{lj}) \times E_p^C \right) X_{lj}^{(i,v')} \right] \quad \forall p \in \{CO_2, SO_2\}. \quad (3)$$

$$\min \sum_{i \in N} \left[\sum_{k \in N} \sum_{v' \in V'} \left(E_f^{(v', LTO)} + R_f^{v', C}(d_{ik}) \right) Z_{ik}^{(v')} + \sum_{k \in N} \sum_{l \in N} \sum_{v \in V} \left(E_f^{(v, LTO)} + R_f^{v, C}(d_{kl}) \right) Y_{kl}^{(i,v)} + \sum_{l \in N} \sum_{j \in N} \sum_{v' \in V'} \left(E_f^{(v', LTO)} + R_f^{v', C}(d_{lj}) \right) X_{lj}^{(i,v')} \right]. \quad (4)$$

$$\min \sum_{v \in V} \sum_{i \in N} \sum_{l \in N} Y_{lb}^{(i,v)} \times 10^{\frac{S_v^L}{10}} + \sum_{v \in V} \sum_{i \in N} \sum_{l \in N} Y_{bl}^{(i,v)} \times 10^{\frac{S_v^T}{10}} + \quad (11)$$

$$\sum_{v' \in V'} \left(\sum_{i \in N, i \neq b} Z_{ib}^{(v')} + \sum_{i \in N} \sum_{j \in N, j \neq b} X_{jb}^{(i,v')} \right) \times 10^{\frac{S_v^L}{10}} + \sum_{v' \in V'} \left(\sum_{i \in N, i \neq b} Z_{bi}^{(v')} + \sum_{i \in N} \sum_{j \in N, j \neq b} X_{bj}^{(i,v')} \right) \times 10^{\frac{S_v^T}{10}} \quad \forall b \in B$$

S.t.

$$\sum_{i \in N} \sum_{k \in N} \sum_{l \in N, l \neq k} Y_{kl}^{(i,v)} \leq y^v \quad \forall v \in V, \quad (14)$$

$$\sum_{i \in N} \sum_{l \in N} \sum_{j \in N, j \neq l} X_{lj}^{(i,v')} + \sum_{i \in N} \sum_{k \in N, k \neq i} Z_{ik}^{(v')} \leq y^v \quad \forall v' \in V'. \quad (15)$$

$$\sum_{v' \in V'} \sum_{k \in N} Z_{ik}^{(v')} t^{v'} = \sum_{j \in N} W_{ij} \quad \forall i \in N, \quad (16)$$

$$\sum_{v' \in V'} \sum_{l \in N} X_{lj}^{(i,v')} t^{v'} = W_{ij} \quad \forall i, j \in N, \quad (17)$$

$$\sum_{v' \in V'} Z_{ik}^{(v')} t^{v'} + \sum_{v \in V} \sum_{l \in N} Y_{lk}^{(i,v)} t^v = \sum_{v \in V} \sum_{l \in N} Y_{kl}^{(i,v)} t^v + \sum_{v' \in V'} \sum_{j \in N} X_{kj}^{(i,v')} t^{v'} \quad \forall i, k \in N, \quad (18)$$

$$\sum_{v' \in V'} Z_{ik}^{(v')} t^{v'} \leq \sum_{j \in N} W_{ij} H_k \quad \forall i, k \in N, \quad (19)$$

$$\sum_{v' \in V'} \sum_{i \in N} X_{lj}^{(i,v')} t^{v'} \leq \sum_{i \in N} W_{ij} H_l \quad \forall l, j \in N, \quad (20)$$

$$X_{lj}^{(i,v')}, Y_{kl}^{(i,v)}, Z_{ik}^{(v')} \geq 0, \quad H_k \in \{0,1\} \quad \forall i, l, j, k \in N.$$

The above multi-objective optimization model is a mixed integer linear programming (MILP) model. Objective function (1) minimizes the total cost of flow and establishing hubs. Objective function (2) minimizes the total VOC , NO_x , and CO emissions in the network. Objective function (3) minimizes the total CO_2 and SO_2 emissions in the network. Objective function (4) minimizes the total fuel burned by aircrafts in the hub-and-spoke network and objective function (11) minimizes the noise at the nodes exposed to the noise pollution. Constraints (14) and (15) are related to the aircraft availability constraint during the peak hour. Constraint (16) ensures that every desired flow from each origin node leaves the origin node. Constraint (17) ensures that all flows for each origin-destination pair arrive at the proper destination. Constraint (18) represents the flows conservation equation at the hubs. Constraints (19) and (20) ensure that there are no direct flows between non-hub nodes.

4. Selected Data and Solver

In this section, we introduce the data set that we use for solving our multi-objective model and we specify the properties of the solver.

4.1. Data

We use the data set that has been used by almost all hub location researchers. This data set was introduced in O'Kelly (1987) and was evaluated by the Civil Aeronautics Board (CAB). It contains information on distances and number of airline passengers between 25 US cities (indicated in Fig. 3) in 1970. This data set is referred to as the CAB data set.

Other often used data sets in literature are the Australia Post (AP) data set based on postal delivery in Sydney including 200 nodes of postal districts (Ernst and Krishnamoorthy, 1996), and the Turkish network (TR) data set based on the cargo flows between 81 cities in Turkey (Tan and Kara, 2007). Due to our focus on air transport, we use the CAB data.

{Please insert Fig. 3 here.}

The total domestic US air passenger flow in 1970 was 153,662,000 (Federal Aviation Administration (FAA), 1979). The CAB data set contains information on passengers between 25 US cities and this information is for 8,540,006 passengers. This data set was collected during the peak month in 1970. Based on this, the flow matrix for the peak hour can be estimated using the coefficient of 10% of the daily flow matrix (de Neufville and Odoni, 2003). The initial values for α and F_k are $\alpha = 0.5$ and $F_k = 500,000 \forall k \in N$, respectively. To obtain insights on the effect of aircraft diversity on the network design we consider multiple aircraft types for each component. Three types of large aircrafts, A320-200, B737-400, and MD82 (100 airplanes of each, i.e., $\forall v', v' \in V': y^{v'} = 100$) are assumed to be used for the collection and distribution components of the network and three types of heavy aircrafts, B767-200ER, B767-300ER, and B757-200 (20 airplanes of each, i.e., $\forall v, v \in V: y^v = 20$) for the transfer component.

The SEL data for each aircraft type are downloaded from the Aircraft Noise and Performance (ANP) database website (<https://www.aircraftnoisemodel.org/>). The data on the emissions and fuel consumption for each aircraft type are available from the EMEP/EEA Guidebook website (www.eea.europa.eu/emep-eea-guidebook). The rest of the required data is obtained from the websites of the manufacturers. Table 2 summarizes the relevant data for the aircrafts.

{Please insert Table 2 here.}

4.2. Solver

The multi-objective optimization problem in Section 3.3.5 is an MILP. Among the MILP solvers, well-known commercial solvers are XPRESS (FICO, 2017), CPLEX (IBM ILOG CPLEX Optimization Studio, 2017), and Gurobi (Gurobi, 2018) while well-known open-source solvers are CBC (Forrest, 2005) and GLPK (Makhorin, 2008). All solvers have been used in the implementation of a vast number of techniques within a branch and cut method. Koch et al. (2013), Jablonský (2015), and Meindl and Templ (2013) compare the performance of selected solvers on test cases taken from the Mixed Integer Programming LIBrary (MIPLIB) from <https://miplib.zib.de/>. This is one of the most important and cited library in the context of MILPs. The comparison shows that three closed source and commercial solvers (GUROBI, XPRESS, and CPLEX) are close in their performance and have better performance than the other solvers with respect to both computation time and number of optimally solved problems (Koch et al., 2013; Jablonský, 2015; Meindl and

Templ, 2013). Further literature research shows that CPLEX is the solver used most by researchers (Koch et al., 2013). Therefore, we choose the CPLEX solver with platform GAMS to solve our MILP.

5. Solution methods

Several methods can be used to solve multi-objective problems. In this section, we introduce multiple methods and report the solutions obtained from each of them. Before elaborating on the methods, we solve the single objective problems. The results are reported in Table 3. Here, f_1 denotes the total cost of flow and establishing hubs, f_2 is the noise level at New York City in A-weighted decibel, f_3 is the total VOC emissions in tonnes, f_4 is the total NO_x emissions in tonnes, f_5 is the total CO emissions in tonnes, f_6 is the total CO_2 emissions in tonnes, f_7 is the total SO_2 emissions in tonnes, and f_8 is the total fuel consumption in tonnes.

{Please insert Table 3 here.}

As can be seen in Table 3 there is no a feasible solution that optimizes all objective functions. Therefore, the multi-objective problem does not have an optimal solution. The results in Table 3 indicate the need for using Multi-Objective Decision-Making (MODM) methods to find the *preferred solution* when all objective functions are considered.

In the rest of the section, we initially introduce the Analytic Hierarchy Process (AHP) method. This method is used in combination of the ϵ -constraint method, the weighted sum method, the weighted min-max method, and the goal-programming method to solve the multi-objective MILP. In Fig. 4, we provide the multi-objective solutions obtained from these methods as well as the classical solution obtained from Ebery et al.'s (2000) model. These solutions tell where the hub and non-hub locations are. In addition, they show the allocation of non-hubs to the hub locations.

{Please insert Fig. 4 here}

5.1. The AHP Method

The AHP, introduced by Saaty (1980), is a proven method for helping decision makers to deal with complex decision-making problems. The AHP incorporates a useful tool for checking the consistency of the decision maker's judgments, thus decreasing the bias in the decision making process. A literature review on Multi-Criteria Decision-Making (MCDM)

techniques concerning transportation decision problems shows that AHP is one of the most applied methods used in more than 25% of the studies (Mardani et al., 2016). We consider the AHP methodology as a complementary approach to the MODM methods used in this study for two reasons. First, the relative importance of the criteria that we consider in this paper is qualitative with sometimes-conflicting assessments of experts. The criteria can be consistently weighted by the AHP method. It enables to translate a group consensus into weights of criteria in a consistent manner (Karaman and Akman, 2017). The priority weights are, in turn, incorporated in the weighted sum, weighted min-max, and goal-programming methods. Second, the AHP method provides a reliable way for selecting among tangible quantitative alternatives obtained by the ε -constraint method with respect to the intangible qualitative criteria weighted by the AHP method.

5.2. The ε -constraint Method

The general form of the multi-objective problem is given in (21):

$$\begin{aligned} \min & \{f_j(x), j = 1, 2, \dots, k\}. \\ \text{S.t.} & \\ & g_i(x) \leq b_i \quad i = 1, 2, \dots, m. \end{aligned} \quad (21)$$

Here, k denotes the number of objective function, $f_j(x)$ denotes the j th objective function ($j = 1, 2, \dots, k$) and $g_i(x)$ denotes the i th constraint of the problem ($i = 1, 2, \dots, m$).

The ε -constraint method minimizes one of the objective functions $f_i(x)$. All other objective functions are used to form additional constraints such that $f_{j(x)} \leq \varepsilon_j, j = 1, \dots, k$ and $j \neq i$. Here, ε_j is the upper bound for objective function $f_j(x)$. In order to arrive at a set of Pareto optimal solutions, a systematic variation of ε_j is done. The lowest and highest values for each objective function $f_j(x)$ are reflected in the tradeoff matrix shown in Table 3, which indicates the range of potentially interesting values for each ε_j . When enough Pareto optimal solutions have been collected, the decision maker selects the preferred solution among them based on priorities that (s)he sets for the objectives. The general mathematical problem studied via this method is given in (22):

$$\begin{aligned} \min & f_i(x). \\ \text{S.t.} & \\ & g_i(x) \leq b_i \quad i = 1, 2, \dots, m, \end{aligned} \quad (22)$$

$$f_j(x) \leq \varepsilon_j \quad j=1,2,\dots,k \text{ and } j \neq i.$$

We select the first objective function f_1 for minimization and the remaining objective functions are subject to constraints.

Different sets of values of ε_j for each Pareto optimal solution are given in Table 4. They are selected based on the results in Table 3. The values of ε_2 were also selected based on the published report of FICON (1992) entitled “Federal Agency Review of Selected Airport Noise Analysis Issues” in which the impacts of aircraft noise on the community in residential areas for several average noise exposure levels are listed. According to this report, hearing loss probably will not occur at 70 dBA but may begin to occur at 75 dBA. Using the commercial package GAMS with the CPLEX solver, the Pareto optimal solutions are obtained. They are reported in Table 5.

{Please insert Tables 4 & 5 here.}

Table 5 is similar to a decision making matrix in which the rows denoted by i and columns denoted by j represent alternatives and criteria, respectively. Elements of the decision-making matrix are denoted by r_{ij} . This matrix is normalized, using the fuzzy normalization described in Equation (23):

n_{ij} : Normalized element r_{ij} .

$$n_{ij} = \frac{\left(\max_i r_{ij}\right) - r_{ij}}{\left(\max_i r_{ij}\right) - \left(\min_i r_{ij}\right)}. \quad (23)$$

The measurement scale in this normalized matrix ranges between 0 and 1 such that 0 represents the worst and 1 represents the best result. The results are shown in Table 6. This table is used in the next subsection to select the final solution of the ε -constraint method.

{Please insert Table 6 here.}

Now, we are facing a Multi-Attribute Decision-Making problem (MADM) with 10 alternatives. Each MADM problem can be broken up into three levels, defined as follows:

- The *overall goal* of the problem is the main objective that drives the decision-making problem.
- The *alternatives* are the options among which the preferred solution is selected.

- The *criteria* of the decision-making problem are the factors that are applied to evaluate the alternatives with respect to the overall goal. Each alternative is judged based on the factors, to find out how well they meet the overall goal.

In our MADM problem, the overall goal is “air transportation network design”, the criteria are $\{f_i, i = 1, \dots, 8\}$ and the alternatives are the 10 Pareto optimal solutions obtained by the ε -constraint method. The grouping AHP approach is used in this section to select the best solution among the Pareto optimal solutions obtained after having applied the ε -constraint method according to the three following steps:

(1) The first step is the organization of the problem as a hierarchy, which should consist of all the relevant aspects of the decision-making problem. The first (or top) level is the overall goal of “air transportation network design”. The second level consists of the eight criteria that contribute to the overall goal. The third (or bottom) level are the ten alternatives evaluated in terms of the criteria. The hierarchy structure is shown in Fig. 5.

{Please insert Fig. 5 here.}

(2) The second step concerns collecting pairwise comparison judgments regarding the relative importance of the criteria with respect to the overall goal. For this purpose, ten experts from the Aeronautics and Astronautics Department of MIT University and the Office of Environment and Energy of the United States Federal Aviation Administration were asked to develop a pairwise comparison matrix of the relative importance of the criteria with respect to the air network design. Assuming the same level of importance among the experts’ opinions, the matrices are integrated.

We use the formula $\frac{\lambda_{max} - n}{n - 1}$ to calculate the consistency ratio. Here, λ_{max} is the maximum eigenvalue of the pairwise comparison and it equals 8.84 in our case. Random index (RI) for $n = 8$ is 1.41. Hence, the consistency ratio is 0.09. Given that this ratio is below 0.1, we can conclude that the inconsistency is at an acceptable level (Saaty, 1980). We eventually obtain the criteria weight vector in Table 7.

{Please insert Table 7 here.}

(3) The third step is to obtain the global priority vector. Multiplying the normalized decision-making matrix presented in Table 6 by the criteria weight vector shown in Table 7 yields the global priority vector for the solutions obtained from applying the ε -constraint method. This vector is in Table 8.

{Please insert Table 8 here.}

Table 8 shows that the third Pareto optimal solution has the largest global priority. Therefore, it is the best solution obtained via the ε -constraint method. Fig. 4 displays the hub-and-spoke network that emerges from this solution.

{ Please insert Fig. 4 here. }

5.3. The Weighted Sum Method

The most common solution method for multi-objective optimization problems is the weighted sum method. The corresponding problem formulation is in (24):

$$\begin{aligned} \min \quad & \sum_{j=1}^k w_j \cdot f_j(x) \\ \text{S.t.} \quad & \\ & g_i(x) \leq b_i \quad i=1,2,\dots,m. \end{aligned} \tag{24}$$

Here, w_j is the AHP weights shown in Table 7 for the relative importance of objective function j such that $\sum_{j=1}^k w_j = 1$ and $w_j > 0 \quad j=1,2,\dots,k$. Since all weights $\{w_j, j=1,2,\dots,k\}$ are positive, (28) is sufficient for Pareto optimality (Zadeh, 1963). Note that the objective functions have different scales and units. Hence, it is necessary to transform them in dimensionless numbers. Equation (25) gives the dimensionless value of objective function j .

$$f_j^{trans}(x) = \frac{f_j(x) - f_j^o}{f_j^o} \tag{25}$$

We have $f_j^o = \min \{f_j(x) \mid g_i(x) \leq b_i \quad i=1,2,\dots,m\}$ as shown in the tradeoff matrix according to Table 3. Then we can rewrite (24) as follows

$$\begin{aligned} \min \quad & \sum_{j=1}^k w_j \cdot f_j^{trans}(x) \\ \text{S.t.} \quad & \\ & g_i(x) \leq b_i \quad i=1,2,\dots,m. \end{aligned} \tag{26}$$

The results obtained by applying the weighted sum method based on (26) are shown in Table 9 and Fig. 4.

{ Please insert Table 9 here. }

5.4. The Weighted Min-Max Method

This method finds a feasible solution minimizing the maximum distance from the ideal solution f_j^o by considering relative importance w_j of each objective. The weighted min-max formulation is as follows:

$$\begin{aligned} \min \quad & \max_{j=1,2,\dots,k} [w_j (f_j(x) - f_j^o)] \\ \text{S.t.} \quad & \\ & g_i(x) \leq b_i \quad i=1,2,\dots,m. \end{aligned} \quad (27)$$

A common approach for dealing with problem (27) is to introduce variable λ and solve the following problem:

$$\begin{aligned} \min \quad & \lambda \\ \text{S.t.} \quad & \\ & w_j (f_j(x) - f_j^o) \leq \lambda \quad j=1,2,\dots,k \\ & g_i(x) \leq b_i \quad i=1,2,\dots,m. \end{aligned} \quad (28)$$

We use the following dimensionless and normalized version of (28):

$$\begin{aligned} \min \quad & \lambda \\ \text{S.t.} \quad & \\ & w_j \cdot f_j^{trans}(x) \leq \lambda \quad j=1,2,\dots,k \\ & g_i(x) \leq b_i \quad i=1,2,\dots,m. \end{aligned} \quad (29)$$

Fig. 4 and Table 9 show the solution of the problem obtained via the weighted min-max method based on (29).

5.5. Goal Programming

Goal programming is one of the most popular and powerful approaches for dealing with multi-objective problems (Hokey and James, 1991). In this method, target levels, L_j are set for all objective functions $f_j(x)$. Weighted goal programming aims to reach a satisfactory solution by minimizing the weighted sum of deviations from the target levels. For the objective function j , we define d_j^+ and d_j^- as the positive and negative deviations from the target levels L_j , respectively. The goal programming formulation is given in (30):

$$\begin{aligned} \min \quad & \sum_{j=1}^k w_j (d_j^+ + d_j^-) \\ \text{S.t.} \quad & \\ & f_j(x) = L_j + d_j^+ - d_j^- \quad j=1,2,\dots,k. \\ & g_i(x) \leq b_i \quad i=1,2,\dots,m. \end{aligned} \quad (30)$$

$$d_j^+, d_j^- \geq 0 \quad j=1,2,\dots,k.$$

As all objective functions concern minimization and the deviations have different scales, we use the customized weighted goal-programming model (31):

$$\begin{aligned} \min & \sum_{j=1}^k w_j \cdot d_j^+ \\ \text{S.t.} & \\ & f_j^{\text{trans}}(x) = \frac{L_j - f_j^o}{f_j^o} + d_j^+ - d_j^- \quad j=1,2,\dots,k. \\ & g_i(x) \leq b_i \quad i=1,2,\dots,m. \\ & d_j^+, d_j^- \geq 0 \quad j=1,2,\dots,k. \end{aligned} \quad (31)$$

Taking into account the values of the takeoff matrix, we selected the following target values $L_1 = 6,500,000$, $L_2 = 70$, $L_3 = 0.6$, $L_4 = 13.5$, $L_5 = 5.5$, $L_6 = 3800$, $L_7 = 1.2$, and $L_8 = 1200$. The result using this method is shown in Table 9 and Fig. 4.

5.6. Preferred Solution

The final solutions obtained with the four methods are summarized in Table 9. None of the solutions dominates the other. Each solution is the best for one or more objective functions. The ε -constraint method performs the best with respect to NO_x , CO_2 , and SO_2 emissions and fuel use. The weighted sum method performs the best for the total cost of flow and establishing hubs, noise level, VOC and SO_2 emissions. The weighted min-max method performs the best for VOC emissions. Finally, the goal programming method performs the best with respect to CO emissions objective. Table 10 shows the normalized decision-making matrix obtained by applying Eq. (23) to results in Table 9.

{Please insert Table 10 here.}

The AHP method can be used to select the preferred solution based on the decision maker's preferences. Table 11 shows the final scores of the solutions that resulted from applying the AHP method. The solution of the ε -constraint and the weighted sum methods have the highest priority and are very close to each other and the decision maker has to choose between these two as a preferred solution.

{Please insert Table 11 here.}

Comparison of subfigures in Fig. 4 shows that the solutions of the new multi-objective model result in more open hubs compared to the classical solution, which relies on cost minimization only. Having more hubs reduces the total distance travelled with passengers and thus the total aircraft-distance in the hub-and-spoke network. This results also in lower

emissions, noise and fuel consumption levels. The total passenger-miles related to the solutions of the multi-objective model according to Table 9 are about 43-44 million miles, while about 51 million miles for the classical solution.

6. Numerical Results

We develop multiple different scenarios to analyze the solutions to our multi-objective optimization model and see how trustworthy its behavior is. For this purpose, we conduct sensitivity analysis on the transfer component factor α and the fixed cost of establishing hub F_k . In addition, we analyze how the greening behavior of the model affects fleet composition by conducting sensitivity analysis on noise level and total VOC emissions upper bounds ε_2 and ε_3 respectively. Given that it is one of the preferred solutions, we consider the ε -constaraint method with $\varepsilon_2 = 70$, $\varepsilon_3 = 0.7$, $\varepsilon_4 = 14$, $\varepsilon_5 = 6.5$, $\varepsilon_6 = 3720$, $\varepsilon_7 = 1.17$ and $\varepsilon_8 = 1180$.

6.1. Effects of the Transfer Component Factor and the Fixed Cost of Establishing Hub

In this section, we consider three values for the transfer component factor α : 0.25, 0.5, and 0.75. For the fixed cost of establishing hub F_k we use the values 500,000 and 50,000 for each node in N . Table 12 shows the optimal solutions for every possible combination of these parameters. The table presents the optimal hub locations and the related optimal value for the total cost of flow and establishing hubs. As expected, when α increases the transfer component cost and the total cost increase. In order to compensate for this increase in the total cost, it is necessary to reduce the number of hubs such that a balance is created between the increasing trends of the flow cost by decreasing the cost for establishing hubs. Increasing the value of $\{F_k, k \in N\}$ leads to the same result; i.e., the number of hubs is reduced to control the total cost.

{Please insert Table 12 here.}

6.2. Effects of Noise Level and Total VOC Emissions Upper Bounds

In this subsection, the effects of parameters ε_2 and ε_3 on the optimal number of needed aircraft types are investigated. $\{n^v, v \in V\}$ and $\{n^{v'}, v' \in V'\}$ are the sets of optimal number of aircrafts for type $v \in V$ and $v' \in V'$ aircrafts, respectively. Values 0.5 and 500,000 are assumed for the parameters α and $\{F_k, k \in N\}$, respectively. The values 66, 68, 70, and 72

1 dBA are considered for parameter ε_2 . In addition, the following percentages change in the
 2 value of ε_3 : +20%, +10%, 0%, -10%, and -20% are considered. For a better understanding of
 3 the related results, we introduce the following theorem.
 4

5 **Theorem I:**

6 Define $\frac{C^v}{t^v}$ and $\frac{C^{v'}}{t^{v'}}$ as the flight cost per passenger for aircraft type $v \in V$ and $v' \in V'$,
 7 respectively. For feasible networks, the total cost is decreasing in the number of heavy and
 8 large aircrafts, i.e., the cost decreases as ratios $\frac{C^v}{t^v}$ and $\frac{C^{v'}}{t^{v'}}$ decrease.
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10 We refer to Appendix B for the proof. According to Theorem I, the preferred solution
 11 tends to select a fleet composition with lower $\frac{C^v}{t^v}$ and $\frac{C^{v'}}{t^{v'}}$ ratios when relative importance
 12 of the cost objective increases.
 13

14 *6.2.1. Effect of ε_2 on n^v and $n^{v'}$*

15 Table 13 presents the preferred fleet composition when ε_2 is set to 66, 68, 70, and 72
 16 dBA.
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18 {Please insert Table 13 here.}

19 Table 14 shows the flight cost per unit distance per passenger seat of the large ($\frac{C^{v'}}{t^{v'}}$) and
 20 heavy ($\frac{C^v}{t^v}$) aircrafts. Table 2 also shows that among the large aircrafts, MD82 has the lowest
 21 noise level while B737-400 and A320-200 produce nearly similar noise levels. Similarly,
 22 among the heavy aircrafts, B757-200 has the lowest noise level whereas B767-200ER and
 23 B767-300ER produce the same noise level.
 24

25 {Please insert Table 14 here.}

26 When ε_2 decreases, in order to satisfy the constraint $f_2 \leq \varepsilon_2$, the use of MD82 increases
 27 in spite of having a higher $\frac{C^{v'}}{t^{v'}}$ ratio. This is because MD82 produces less noise than the other
 28 large aircraft types. When ε_2 increases, the constraint $f_2 \leq \varepsilon_2$ is further relaxed, and hence, the
 29 use of A320-200 increases while the use of MD82 decreases because A320-200 has a lower
 30 $\frac{C^{v'}}{t^{v'}}$ ratio than MD82. Hence, according to Theorem I, the total cost decreases.
 31

Among the heavy aircrafts, the use of B757-200 is always maximal because it has the lowest noise level and the lowest $\frac{C^v}{t^v}$ ratio. Compared to B767-200ER, aircraft B767-300ER is preferred due to the equal noise level but lower $\frac{C^v}{t^v}$ ratio. Another observation is that when $\varepsilon_2 \geq 72$, the constraint $f_2 \leq \varepsilon_2$ becomes redundant.

6.2.2. Effect of ε_3 on n^v and $n^{v'}$

Table 15 shows preferred fleet composition when percentages change of +20%, +10%, 0%, -10%, and -20% are considered for VOC emissions upper bound.

{Please insert Table 15 here.}

According to Table 2, the VOC emitted per LTO cycle is the smallest for B737-400 among the large aircrafts types and roughly the same for MD82 and A320-200. Among the heavy aircraft types, the smallest value is reported for both B767-200ER and B767-300ER and the largest value for B757-200. As suggested by Fig. 6, ranking the aircrafts based on the amount of VOC emissions generated during the same flight distance in the cruise cycle gives in ascending order B737-400, A320-200, and MD82 for the large aircrafts and B767s followed by B757-200 for the heavy aircrafts.

{Please insert Fig. 6 here.}

According to Table 15, when ε_3 increases, the use of aircraft A320-200 among the large aircrafts and B757-200 among the heavy ones is more due to the lower values of $\frac{C^{v'}}{t^{v'}}$ and $\frac{C^v}{t^v}$, respectively. These results are supported by Theorem I. Furthermore, in order to satisfy the constraint $f_3 \leq \varepsilon_3$, the use of aircraft B737-400 increases when ε_3 decreases because B737-400 is associated with lower VOC emissions compared to the other large aircrafts. When ε_3 decreases, the use of B757-200 among the heavy aircrafts reduces despite the associated lower $\frac{C^v}{t^v}$ ratio due to higher VOC emissions. However, to satisfy the constraint $f_3 \leq \varepsilon_3$, aircrafts B767-300ER and B767-200ER are used more often when ε_3 decreases.

7. Assessment of the New Measure

1 The objective of this section is to estimate the contribution of the new measure for
2 achieving sustainable targets compared to the classical model. For this purpose, we derive the
3 cumulative Marginal Abatement Cost (MAC) curves for reducing CO_2 emissions in the
4 domestic US aviation sector between 2020 and 2050 using the new measure for constructing
5 the air transportation network. The MAC curve is defined as a graph representing the cost per
6 tonne of an emission generally CO_2 , associated with the last unit (the marginal cost) of the
7 emission reduction for different amounts of emission abatement usually in million tonnes
8 (Kesicki and Strachan, 2011).
9

10 We assume that our solution is started to be implemented in 2020 with a target of
11 achieving the objectives set by aviation authorities for 2050. We use the CAB data set and
12 assume that the demand flow patterns between cities remain unchanged. We remove the
13 aircraft availability constraints during peak hours, because we implement the multi-objective
14 model annually. Fig. 7 shows the number of annual domestic US air passengers in the period
15 from 1970 to 2017 (FAA, 1979, 1989, 1996; Bureau of Transportation Statistics (BTS),
16 2019). The number of domestic US air passengers is projected to increase by 4.7% in 2018
17 and then grow on average 1.7% annually during 2019-2038 (FAA, 2018). We assume that
18 this annual growth rate continues until 2050.
19

20 {Please insert Fig. 7 here.}
21

22 We create a baseline curve for the projected annual CO_2 emissions using the results in
23 Ebrey et al. (2000). The baseline curve is depicted in Fig. 8. We consider improvements in
24 the emission level from 1% to 20% with an increment of 1%. As a mitigation cost metric, we
25 employ the cumulative marginal abatement cost from 2020 to 2050, discounted to 2020 at a
26 rate of 5% expressed in US\$ per tonne of CO_2 saved and calculated by dividing the Net
27 Present Value (NPV) of the cost by the total reduction in CO_2 emissions over the period of
28 the assessment. We consider jet fuel prices of US\$3.1 and US\$2.0 per gallon corresponding
29 with crude oil prices of about US\$100 and US \$50 per barrel respectively (Schäfer et al.,
30 2016). The negative and zero marginal costs represent cost-effective and economically
31 attractive mitigation opportunities from the aviation industry point of view.
32

33 Fig. 9 shows the cumulative MAC curves and cost-effectiveness of the various
34 improvement at jet fuel prices of US\$3.1 and US\$2.0 per gallon. The baseline CO_2 leads to
35 cumulative CO_2 emissions of 2.523 billion tonnes for the CAB data set. According to the
36 cumulative MAC curves, taking into account only the CO_2 emissions reduction with negative
37 or zero marginal costs, the projected cumulative CO_2 emissions from 2020 to 2050 would
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decline by about 250 and 200 million tonnes (equivalent to ~ 10% and 8%) compared to the classical model at jet fuel prices of US\$3.1 and US\$2.0 per gallon respectively. Fig. 8 also represents the projected annual CO_2 emissions of the domestic US aviation for both jet fuel prices (For details, see Supplementary Information).

{Please insert Figs. 8 and 9 here.}

Even larger improvements can be justified in case of a market-based mechanism such as Emission Trading Schemes (ETS) and carbon tax systems. ETS refers to a cap-and-trade system or variants of it (baseline-and-credit and baseline-and-offset) as implemented in the European Union, New Zealand, China, and Australia. In the context of these schemes, the airlines get a certain amount of emission permission over a planning horizon (Yang et al., 2018; Ortas and Álvarez, 2016). The airlines that have more permits than they need, can save them for future use or can sell them to others. The airlines that need more permits can buy them from other carriers. The carbon tax systems charge the airlines for their carbon emissions at a constant tax rate (He et al., 2015). These systems have already been implemented in Argentina and scheduled for implementation in South Africa. The above-mentioned mechanisms motivate the airlines even more to invest in the green hub-and-spoke networks. This motivation implies wide applicability of the measure that is proposed in this paper. Considering the external costs of environmental impact, which includes human health, ecosystems, resource depletion and global warming, adds to the value of our measure (Dings et al., 2003; Hendriks et al., 2006).

We conclude that the new mitigation measure is cost-effective, economically attractive and can play an important role in achieving future sustainability.

8. Conclusions

In the light of the growing problems related to air transportation emissions, fuel consumption, and noise, aviation authorities and industries adopted ambitious targets for carbon emissions reduction and energy saving and are strictly controlling generated noise and GHG by aircrafts. We contributed to the goal of achieving these targets by defining a measure based on a multi-objective mixed integer linear programming model in the context of hub location problem for airlines hub-and-spoke networks. We extended the classical model in Ebery et al. (2000) by taking into account the fleet composition and minimizing different GHG emissions, noise pollution and fuel consumption. We solved the multi-objective model using multiple MODM approaches including ε -constraint, weighted sum,

weighted min-max, and goal-programming methods in combination with the grouping AHP approach. We concluded that the solutions provided by the ε -constraint and the weighted sum methods are the preferred solutions. We performed sensitivity analysis on multiple system parameters and analyze the changes in the preferred solution.

We estimated the contribution of the new measure for achieving sustainable targets compared to the classical model. For this purpose, we derived the cumulative Marginal Abatement Cost (MAC) curves for reducing CO_2 emissions in the domestic US aviation sector between 2020 and 2050 by using the new measure for constructing the air transportation network. Our findings show that developed measure could cost-effectively reduce the projected cumulative CO_2 emissions by almost 10% and 8% at jet fuel prices of US\$3.1 and US\$2.0 per gallon, respectively. Our research not only provides a useful tool for the airlines but also aviation authorities such as IATA, ICAO, FAA, and ACARE, which aim to achieve sustainable targets.

Future research can consider relaxing the assumption of no direct service between two non-hub nodes. Additional objectives related to the eco-costs and travelling time can be studied. Comparing the new method with other mitigation measures can be another future research idea.

Appendix A. Notation

Indexes:

$N = \{1, \dots, n\}$ Set of nodes,

$V = \{v_1, v_2, \dots, v_{|V|}\}$ Set of heavy passenger aircraft types,

$V' = \{v'_1, v'_1, \dots, v'_{|V'|}\}$ Set of large passenger aircraft types,

$U = V \cup V'$ Set of all aircraft types,

$|V|$ Number of heavy aircraft types,

$|V'|$ Number of large aircraft types,

P Set of aircraft pollutant species, $P = \{VOC, NO_x, CO, CO_2, SO_2\}$, and

B Set of nodes exposed to noise pollution.

Parameters:

W_{ij}	Flow of passengers from node i to node j ,
d_{ij}	Euclidian distance between nodes i and j ,
F_k	Fixed cost for establishing a hub at node k ,
χ	Cost factor of collection component,
α	Discount factor of transfer component,
δ	Cost factor of distribution component,
c^u	Flight cost of an aircraft of type $u \in U$ per unit distance,
$E_p^{(u, LTO)}$	Amount of pollutant $p \in P$ emitted by an aircraft of type $u \in U$ per LTO cycle,
$E_f^{(u, LTO)}$	Fuel consumption of an aircraft of type $u \in U$ per LTO cycle,
E_p^C	Amount of pollutant $p \in \{CO_2, SO_2\}$ emitted per unit fuel burnt during the cruise cycle,
$R_p^{u,C}(d_{ij})$	Amount of pollutant $p \in \{VOC, NO_x, CO\}$ emitted by an aircraft of type $u \in U$ during flight distance d_{ij} in the cruise cycle,
$R_f^{u,C}(d_{ij})$	Amount of fuel used by an aircraft of type $u \in U$ during flight distance d_{ij} in the cruise cycle,
S_u^L	Average SEL emitted by an aircraft of type $u \in U$ while landing in A-weighted decibel,
S_u^T	Average SEL emitted by an aircraft of type $u \in U$ during takeoff in A-weighted decibel,
τ	The reference time for ψ_b in seconds,
y^u	Number of available aircrafts of type $u \in U$ during the peak hour for the airline, and
t^u	Capacity of an aircraft of type $u \in U$ in number of passenger seats.

Decision variables:

$Z_{ik}^{(v')}$	Number of flights using an aircraft of type $v' \in V'$ from origin i to hub k (collection component),
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$Y_{kl}^{(v)}$	Number of flights using an aircraft of type $v \in V$ from hub k to hub l (transfer component) for flow originating at origin i ,
$X_{lj}^{(i,v')}$	Number of flights using an aircraft of type $v' \in V'$ from hub l to destination j (distribution component) for flow originating at origin i , and
H_k	$\begin{cases} 1 & \text{if node } k \text{ is a hub,} \\ 0 & \text{otherwise.} \end{cases}$

Dependent variables:

ψ_b	Equivalent noise level at node b in A-weighted decibel,
$\lambda_b^{(u,L)}$	Number of landing aircrafts of type $u \in U$ at node $b \in B$,
$\lambda_b^{(u,T)}$	Number of departing aircrafts of type $u \in U$ at node $b \in B$,
n^v	Number of needed aircrafts of type $v \in V$ for the transfer component (between hub nodes) during peak hour, and
$n^{v'}$	Number of needed aircrafts of type $v' \in V'$ for the collection and distribution components (between non-hub and hub nodes) during peak hour.

Objectives:

f_1	Total cost of flow and establishing hubs,,
f_2	Equivalent noise level at New York City in A-weighted decibel,
f_3	Total VOC emissions in tonnes,
f_4	Total NO_x emissions in tonnes,
f_5	Total CO emissions in tonnes,
f_6	Total CO_2 emissions in tonnes,
f_7	Total SO_2 emissions in tonnes, and
f_8	Total fuel consumption in tonnes.

Appendix B. Proof of Theorem I

Rank the heavy aircrafts in $V^{(i)} = \{v^{(1)}, v^{(2)}, \dots, v^{(|V|)}\}$ such that

$$\frac{c^{v^{(1)}}}{t^{v^{(1)}}} < \frac{c^{v^{(2)}}}{t^{v^{(2)}}} < \dots < \frac{c^{v^{(|V|)}}}{t^{v^{(|V|)}}. \quad (\text{B.1})$$

Rank the large aircraft in $V^{(j)} = \{v^{(1)}, v^{(2)}, \dots, v^{(|V|)}\}$ such that

$$\frac{c^{v^{(1)}}}{t^{v^{(1)}}} < \frac{c^{v^{(2)}}}{t^{v^{(2)}}} < \dots < \frac{c^{v^{(|V|)}}}{t^{v^{(|V|)}}. \quad (\text{B.2})$$

Now, variables $\zeta_{collection}$, $\zeta_{transfer}$, $\zeta_{distribution}$, ζ_{flow} , ζ_{total} , $Z_{ik(v')}$, $Y_{kl(v)}$ and $X_{lj(v')}$ are defined as follows:

$\zeta_{collection}$: Collection component cost,

$\zeta_{transfer}$: Transfer component cost,

$\zeta_{distribution}$: Distribution component cost,

ζ_{flow} : Flow cost,

ζ_{total} : Total cost,

$Z_{ik(v')}$: Number of passengers traveling from node i to hub k using large aircraft $v' \in V'$ (corresponding to the collection component),

$Y_{kl(v)}$: Number of passengers traveling from hub k to hub l that start at origin i using heavy aircraft $v \in V$ (corresponding to the transfer component), and

$X_{lj(v')}$: Number of passengers traveling from hub l to node j that start at origin i using large aircraft $v' \in V'$ (corresponding to the distribution component).

Then

$$Z_{ik(v')} = Z_{ik}^{(v')} \times t^{v'}, \quad (\text{B.3})$$

$$Y_{kl(v)} = Y_{kl}^{(i,v)} \times t^v, \quad (\text{B.4})$$

$$X_{lj(v')} = X_{lj}^{(i,v')} \times t^{v'}, \quad (\text{B.5})$$

Then

$$\begin{aligned} \zeta_{collection} &= \sum_{v'} \sum_i \sum_k \chi c^{v'} d_{ik} Z_{ik}^{(v')} \xrightarrow{\text{Using Relation (A.3)}} \zeta_{collection} = \sum_{v'} \sum_i \sum_k \chi c^{v'} d_{ik} \frac{Z_{ik(v')}}{t^{v'}} = \\ &\chi \frac{c^{v^{(1)}}}{t^{v^{(1)}}} \sum_i \sum_k d_{ik} Z_{ik(v^{(1)})} + \chi \frac{c^{v^{(2)}}}{t^{v^{(2)}}} \sum_i \sum_k d_{ik} Z_{ik(v^{(2)})} + \dots + \chi \frac{c^{v^{(|V|)}}}{t^{v^{(|V|)}}} \sum_i \sum_k d_{ik} Z_{ik(v^{(|V|)})}, \end{aligned} \quad (\text{B.6})$$

$$\zeta_{transfer} = \sum_v \sum_i \sum_k \sum_l \alpha c^v d_{kl} Y_{kl}^{(i,v)} \xRightarrow{\text{Using Relation (A.4)}} \zeta_{transfer} = \sum_v \sum_i \sum_k \sum_l \alpha c^v d_{kl} \frac{Y_{kl}^{(i)}(v)}{t^v} = \quad (B.7)$$

$$\alpha \frac{c^{v^{(1)}}}{t^{v^{(1)}}} \sum_i \sum_k \sum_l d_{kl} Y_{kl}^{(i)}(v^{(1)}) + \alpha \frac{c^{v^{(2)}}}{t^{v^{(2)}}} \sum_i \sum_k \sum_l d_{kl} Y_{kl}^{(i)}(v^{(2)}) + \dots + \alpha \frac{c^{v^{(|V|)}}}{t^{v^{(|V|)}}} \sum_i \sum_k \sum_l d_{kl} Y_{kl}^{(i)}(v^{(|V|)}),$$

$$\zeta_{distribution} = \sum_{v'} \sum_l \sum_j \sum_i \delta c^{v'} d_{lj} X_{lj}^{(i,v')} \xRightarrow{\text{Using Relation (A.5)}} \zeta_{distribution} = \sum_{v'} \sum_l \sum_j \sum_i \delta c^{v'} d_{lj} \frac{X_{lj}^{(i)}(v')}{t^{v'}} = \quad (B.8)$$

$$\delta \frac{c^{v^{(1)}}}{t^{v^{(1)}}} \sum_l \sum_j \sum_i d_{lj} X_{lj}^{(i)}(v^{(1)}) + \delta \frac{c^{v^{(2)}}}{t^{v^{(2)}}} \sum_l \sum_j \sum_i d_{lj} X_{lj}^{(i)}(v^{(2)}) + \dots + \delta \frac{c^{v^{(|V|)}}}{t^{v^{(|V|)}}} \sum_l \sum_j \sum_i d_{lj} X_{lj}^{(i)}(v^{(|V|)}),$$

$$\zeta_{flow} = \zeta_{collection} + \zeta_{transfer} + \zeta_{distribution}, \quad (B.9)$$

$$\zeta_{total} = \zeta_{flow} + \sum_k F_k H_k. \quad (B.10)$$

And

$$Y_{kl}^i = \sum_v Y_{kl}^{(i,v)} = Y_{kl}^{(i)}(v^{(1)}) + Y_{kl}^{(i)}(v^{(2)}) + \dots + Y_{kl}^{(i)}(v^{(|V|)}), \quad (B.12)$$

$$X_{lj}^i = \sum_{v'} X_{lj}^{(i)}(v') = X_{lj}^{(i)}(v^{(1)}) + X_{lj}^{(i)}(v^{(2)}) + \dots + X_{lj}^{(i)}(v^{(|V|)}). \quad (B.13)$$

Based on the above equations, we can conclude that in order to minimize total cost (ζ_{total}) in a feasible network, priority should be given to heavy and large aircrafts according to the lower ratio of $\frac{c^{v^{(i)}}}{t^{v^{(i)}}}$ and $\frac{c^{v^{(j)}}}{t^{v^{(j)}}}$ respectively. $\square$

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Table 1. Input data and tools required for the three Tiers (EEA, 2016)

Tier	Data/tools used
Tier 1	Total amount of fuel consumption for domestic and international flights separately, Total LTO numbers for domestic and international flights separately, and Average fleet mix (i.e. generic aircraft emission factors) and average factors for LTO and cruise cycles.
Tier 2	Total amount of fuel consumption for domestic and international flights separately, LTO numbers per aircraft type for domestic and international flights separately, and Aircraft specific LTO cycle emission factors and average emission factors for cruise cycle.
Tier 3	Data for each flight including aircraft type and flight distance for domestic and international flights separately. Tier 3A: Specific aircraft type/engine data from the spreadsheet available EEA (2016). Tier 3B: US FAA Aviation Environmental Design Tool (AEDT), EUROCONTROL Advanced Emission Model (AEM) or similar tools with specific airport taxi times.

Table 2. Some technical characteristics of the aircraft types

Manufacturer	Aircraft Model	Aircraft type	Capacity (in passengers)	SEL (dBA)		Flight cost (\$/mile)	$EF_{VOC}^{(u,LTO)}$ (gram/LTO)
				Approach	Departure		
Airbus	A320-200	Large	150	84.2	88.4	13.534	1923.2
Boeing	B737-400	Large	147	85	87.6	16.573	666.8
McDonnell Douglas	MD 82	Large	143	81.7	86.6	16.837	1915.5
Boeing	B767-200ER	Heavy	181	87.4	89.3	22.849	881
Boeing	B767-300ER	Heavy	218	87.4	89.3	23.826	881
Boeing	B757-200	Heavy	200	84.6	85.3	19.587	1232.5

Table 3. Tradeoff matrix

Objectives	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
$\min f_1$	4,039,074.86	71.94	1.08	19.68	6.26	4,567.04	1.45	1,449.85
$\min f_2$	17,511,829.03	66.02	1.19	28.69	7.43	7,063.70	2.24	2,242.44
$\min f_3$	15,274,600.66	69.49	0.43	14.06	6.37	3,957.73	1.25	1,256.43
$\min f_4$	15,295,973.75	69.21	0.46	12.78	6.24	3,662.65	1.16	1,162.76
$\min f_5$	15,183,416.29	68.36	0.96	16.28	4.43	4,224.32	1.34	1,341.03
$\min f_6$	14,986,275.41	69.22	0.76	14.13	7.15	3,454.59	1.09	1,096.72
$\min f_7$	14,986,275.41	69.22	0.76	14.13	7.15	3,454.59	1.09	1,096.72
$\min f_8$	14,986,275.41	69.22	0.76	14.13	7.15	3,454.59	1.09	1,096.72

Table 4. Different sets of values of ε_j for each Pareto optimal solution

Pareto optimal solution	ε_2	ε_3	ε_4	ε_5	ε_6	ε_7	ε_8
1	70	0.80	15.00	6.00	3,900.00	1.30	1,350.00
2	69	0.85	16.00	7.00	3,800.00	1.25	1,300.00
3	70	0.70	14.00	6.50	3,720.00	1.17	1,180.00
4	68	0.60	17.00	7.50	4,000.00	1.25	1,200.00
5	69	0.75	14.50	6.00	3,950.00	1.27	1,300.00
6	69	0.95	16.00	6.00	3,900.00	1.30	1,400.00
7	68	0.90	15.50	7.00	3,850.00	1.35	1,380.00
8	68	0.70	15.00	7.00	4,000.00	1.50	1,450.00
9	70	0.60	14.00	6.50	3,800.00	1.25	1,200.00
10	69	0.65	17.00	5.50	3,850.00	1.40	1,450.00

Table 5. Pareto optimal solutions obtained by the ε -constraint method

Pareto optimal solution	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
1	5,237,624.18	69.00	0.63	15.00	6.00	3,816.07	1.21	1,211.46
2	5,000,780.77	69.51	0.85	15.87	7.00	3,800.00	1.20	1,206.36
3	6,615,403.04	68.00	0.59	14.00	6.28	3,707.04	1.17	1,176.84
4	5,631,926.90	69.00	0.60	15.03	6.25	3,779.98	1.19	1,200.00
5	5,726,363.72	69.00	0.60	14.50	6.00	3,756.64	1.19	1,192.59
6	4,960,065.44	68.00	0.82	16.00	6.00	3,878.20	1.23	1,231.17
7	5,052,620.58	69.69	0.69	15.50	6.39	3,850.00	1.22	1,222.23
8	5,247,987.29	68.00	0.65	15.00	6.27	3,898.66	1.23	1,237.68
9	6,240,002.98	69.00	0.57	14.00	6.23	3,755.46	1.19	1,192.22
10	6,716,458.66	69.00	0.65	14.55	5.50	3,790.72	1.20	1,203.40

Table 6. Normalized decision-making matrix related to the ε -constraint method

Pareto optimal solution	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
1	0.84	0.04	0.79	0.50	0.67	0.43	0.33	0.43
2	0.98	0.39	0.00	0.07	0.00	0.51	0.50	0.51
3	0.06	0.08	0.93	1.00	0.48	1.00	1.00	1.00
4	0.62	1.00	0.89	0.49	0.50	0.62	0.67	0.62
5	0.56	0.39	0.89	0.75	0.67	0.74	0.67	0.74
6	1.00	0.39	0.11	0.00	0.67	0.11	0.00	0.11
7	0.95	1.00	0.57	0.25	0.41	0.25	0.17	0.25
8	0.84	1.00	0.71	0.50	0.49	0.00	0.00	0.00
9	0.27	0.00	1.00	1.00	0.51	0.75	0.67	0.75
10	0.00	0.39	0.71	0.73	1.00	0.56	0.50	0.56

Table 7. Criteria weight with respect to the overall goal

Criteria	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
weight	0.08	0.07	0.12	0.20	0.13	0.11	0.16	0.13

Table 8. Alternatives scores for the solutions obtained with the ε -constraint method

Solution	1	2	3	4	5	6	7	8	9	10
Score	0.51	0.32	0.78	0.65	0.70	0.23	0.4	0.39	0.70	0.6

Table 9. Final solutions obtained with the four methods

Methods	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
ε -constraint	6,615,403.04	69.51	0.59	14.00	6.28	3,707.04	1.17	1,176.84
Weighted Sum	6,173,401.75	68.03	0.58	14.40	6.20	3,720.34	1.17	1,181.07
Weighted Min-Max	6,341,860.71	68.20	0.58	14.41	5.88	3,882.73	1.23	1,232.61
Goal Programming	6,775,717.91	69.34	0.60	14.05	5.70	3,780.00	1.19	1,200.00

Table 10. Normalized decision-making matrix

Methods	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
ε -constraint	0.27	0.00	0.50	1.00	0.00	1.00	1.00	1.00
Weighted Sum	1.00	1.00	1.00	0.02	0.14	0.92	1.00	0.92
Weighted Min-Max	0.72	0.89	1.00	0.00	0.69	0.00	0.00	0.00
Goal Programming	0.00	0.11	0.00	0.88	1.00	0.58	0.67	0.58

Table 11. Final scores for the solutions of the four methods determined via the AHP

ε -Constraint	Weighted Sum	Weighted Min-Max	Goal Programming
0.68	0.67	0.33	0.56

Table 12. Effects of the parameters α and F_k

α	F_k			
	50,000		500,000	
	Hub locations	Total cost	Hub locations	Total cost
0.25	1, 4, 7, 8, 9, 12, 14, 17, 21, 22, 25	2,805,569.78	1, 4, 7, 9, 12, 14, 17, 22, 25	6,557,587.58
0.5	1, 4, 7, 8, 9, 12, 14, 17, 22, 25	2,944,574.43	4, 7, 9, 12, 14, 17, 22, 25	6,615,403.04
0.75	1, 4, 7, 8, 9, 12, 14, 17, 22, 25	3,024,280.82	4, 7, 9, 12, 14, 17, 22, 25	6,651,911.57

Table 13. Effects of ε_2 on n^v and $n^{v'}$

Percentage change in ε_2	v'			v		
	$n^{A320-200}$	$n^{B737-400}$	n^{MD82}	$n^{B767-200ER}$	$n^{B767-300ER}$	$n^{B757-200}$
66	47.106	20.304	100	0	14.001	20
68	73.085	52.831	40.953	0	14.939	20
70	80.314	59.009	26.702	0	15.062	20
≥ 72	100	64.151	0	0	17.694	20

Table 14. Flight cost per unit distance per passenger seat

Aircraft type	Aircraft model	$\frac{C^v}{t^v}$	Aircraft type	Aircraft model	$\frac{C^{v'}}{t^{v'}}$
heavy	B767-200ER	0.126	large	A320-200	0.090
	B767-300ER	0.109		B737-400	0.113
	B757-200	0.098		MD82	0.118

Table 15. Effects of ε_3 on $n^{v'}$ and n^v

Percentage change in ε_3	v'			v		
	$n^{A320-200}$	$n^{B737-400}$	n^{MD82}	$n^{B767-200ER}$	$n^{B767-300ER}$	$n^{B757-200}$
-20	66.034	100	0	2.406	20	12.767
-10	75.228	86.104	4.612	0	18.092	17.355
0	80.314	59.009	26.702	0	15.062	20
+10	89.160	56.693	20.100	0	16.032	20
+20	95.028	53.992	14.472	0	17.544	20

Figure captions to illustration:

Fig. 1. Emission mitigation measures

Fig. 2. Typical phases of flight (Intergovernmental Panel on Climate Change (IPCC), 2000)

Fig. 3. CAB data set (Marianov and Serra, 2003)

Fig. 4. Hub-and-spoke network obtained with different solution methods

Fig. 5. Hierarchical structure

Fig. 6. VOC emitted by the aircrafts against flight distance in the cruise cycle

Fig. 7. Historical data for the number of domestic US air passengers from 1970 to 2017
(FAA, 1979, 1989, 1996; BTS, 2019)

Fig. 8. Projected annual CO_2 emissions for the period 2020-2050

Fig. 9. Cumulative MAC curves based on the new measure

Airline Operational Strategies

- Reducing contingency fuel (2015, -106)
- Fleet planning and early replacements of aircraft older than 25 years (2020, +61)
- Increased passenger load factor by reduced flight frequency (2025, -115)
- Increased passenger load factor by better matching of aircraft type to mission (2025, +2193)
- Reduced fuel tankering (2015, +1627)
- Additional engine wash (2015, -53)
- Surface polish and reduced decorative paint (2015, +1770)
- Airline hub-and-spoke network**
(New measure in this paper)

Air Traffic Management Measures

- Surface congestion management (2020, -86)
- Single-engine taxi (2015, -105)
- Optimized departures procedures (2020, -57)
- Inefficiency reduction during cruise (2020, -88)
- Optimized approach procedures (2020, -57)

Sustainable Alternative Fuels: Biofuel
(2020, Depending on jet fuel price)

Technology Measures

Retrofit measures

- Blended winglets (2015, -102)
- Carbon brakes (2015, +2)
- Re-engining (2016, +82)
- Cabin weight reduction (2015, -58)
- Electric taxiing (2018, -105)

New aircrafts

- Intermediate-generation aircraft types (2016, -37)
- Next-generation aircraft types by new evolutionary design (2035, -45)
- Next-generation aircraft types by CRP design (2035, -53)

Positive Economic Measures

- Emission trading scheme (ETS)
- Carbon tax
- Market based measures (MBM)
- Green taxes
- Fuel levies

Green Aviation

Fig. 1. Emission mitigation measures

The numbers in the parentheses indicate (Year of introduction, Mitigation cost US\$ per tonne of CO_2) (Schäfer et al., 2016)

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Fig. 2. Typical phases of flight (Intergovernmental Panel on Climate Change (IPCC), 2000)

1 ATLANTA	14 MIAMI
2 BALTIMORE	15 MINNEAPOLIS
3 BOSTON	16 NEW ORLEANS
4 CHICAGO	17 NEW YORK
5 CINCINNATI	18 PHILADELPHIA
6 CLEVELAND	19 PHOENIX
7 DALLAS-FW	20 PITTSBURGH
8 DENVER	21 ST. LOUIS
9 DETROIT	22 SAN FRANCISCO
10 HOUSTON	23 SEATTLE
11 KANSAS CITY	24 TAMPA
12 LOS ANGELES	25 WASHINGTON
13 MEMPHIS	

Fig. 3. CAB data set (Marianov and Serra, 2003)

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Classical solution

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Solution of the ε -constraint method

Solution of the weighted sum method

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Solution of the weighted min-max method

Solution of the goal programming method

Fig. 4. Hub-and-spoke network obtained with different solution methods

Notice: Fig. 4 is a color figure.

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Fig. 5. Hierarchical structure

Fig. 6. VOC emitted by the aircrafts against flight distance in the cruise cycle

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Notice: Figs. 8 is a color figure.

Fig. 9. Cumulative MAC curves based on the new measure

Supplementary File

[Click here to download Supplementary File: Supplementary Information.xls](#)

Interest Rate	5%
Fuel Price (US\$/Gallon)	3.10
Convert tonne to gallon jet fuel	329.05