Electric Aviation Optimization: Network design for emergent electric aviation technologies

Johanna Skåntorp[1], Alicia Palmqvist[1], Jennifer Liu[1], Andrea Ruglioni[2], and Marcus Söderholm[1]

[1] KTH - Royal Institute of Technology, Stockholm, Sweden
{skanto, aliciapa, jenliu, mso4}@kth.se
[2] Polytechnic University of Turin, Italy
{andrea.ruglioni}@studenti.polito.it

Abstract. This paper introduces an innovative approach to aviation network design, taking into consideration a diverse fleet of aircraft with varying capacities and maximum travel distances. The model presented in this research aims to adapt to the emergence of electric aviation technologies, challenging the conventional Hub-and-Spokes (H&S) network design paradigm. The findings illustrate how the model handles scenarios involving either increased landing costs or heightened demand. Additionally, this report explores practical implications associated with implementation, including the necessity for adaptable infrastructure and the impact of evolving passenger preferences within the dynamic electric transportation industry. Future research could explore the integration of elements from the H&S model into the proposed approach and incorporate additional factors, such as infrastructural costs, to provide a more comprehensive and realistic perspective.

Keywords: Mixed-Integer Linear Programming · Electric Aviation · Multi-Commodity Flow Network · Swedish Aviation

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1 Introduction

Electric aviation is emerging as a fundamental component of Sweden's commitment to combating Greenhouse Gas (GHG) emissions. In the face of global warming and the pressing need to reduce GHG emissions, Sweden has set a pioneering objective of having no net GHG emissions by 2045, with the aim of domestic emissions reductions of a minimum of 85% compared to 1990.[10] One transformative initiative in Sweden's climate agenda is electric aviation. With an emphasis on transportation-related emissions, incorporating electric aircraft into the transportation infrastructure could potentially revolutionize the way people and goods move, reducing the reliance on fossil fuels and mitigating the environmental impact of aviation.[10]

In the past, when making strategic decisions regarding the optimization of aviation networks, the Hub-and-Spokes (H&S) model has traditionally been the primary approach. H&S models generally consolidate the flow from various origins to a subset of airports, referred to as hubs, which serve as central points. Flights then depart from these hubs to reach their final destinations. Non-hub airports are are known as spokes. The aim is to determine optimal routes and flight schedules, to maximize efficiency, minimize costs, and create good air connectivity by strategically positioning hubs and plan the best flight paths. [5]

However, due to emerging technologies, traditional H&S models might become less relevant. Today, the Swedish aviation network function much like H&S, with Arlanda as the main hub; via which low-demand origin-destination pairs are routed. Flying from Luleå to Gällivare currently requires a stop-by in Stockholm. Unsurprisingly the motivation behind this is profitability. Not enough people want to travel the Luleå-Gällivare leg in a day to justify a point-to-point connection. An increased availability of relatively cheap, low capacity air-crafts, have the possibility to change this equation.

A heterogeneous air-fleet, both with respect to capacity and operational cost, as well as reach, is not generally considered in H&S optimization. To account for the introduction of electrical air-crafts we propose an alternative model for designing future aviation networks, by building on the model by [8]. Instead of relying on models which treats airline network design as a hub-location problem, the problem is instead approached as a Multi-Commodity Network Flow (MCNF) problem. The model, while allowing for the choice of different air-crafts, does not specifically seek to construct an H&S-network.

The outline of the present article is as follows: In section 1 the problem is introduced and explained and section 2 gives a broader knowledge of it.

In Section 3.1 we present the model by [8], after which we motivate and present our own model in Section 3.2. Some variations of the model is covered. The model is tested and a visualization of the solutions is presented in Section 5. Section 6 covers the limitations of the data and addresses the implications of the results and potential areas for future research. Lastly, a conclusion is presented in Section 7.

1.1 Purpose, Aim and Motivation

Current aviation network design is based on the H&S model. The purpose of this paper is to consider ways of incorporating the varied nature of future air-fleets into a model that would redesign the Swedish aviation network. Additionally, the aim is to identify the implications of a reshaped model as well as potential gaps within the research for future research.

1.2 Research Question

The objective of this research is to make significant progress in addressing the central inquiry regarding the potential impact of electric aviation technologies on Sweden's aviation network. Our primary contribution will involve the development and empirical testing of a model designed for the purpose of shaping aviation networks. Thus, answering the following research question:

How can the integration of emerging electric aviation technologies transform Sweden's aviation network structure and operations, departing from the traditional H&S model, to contribute to greenhouse gas reduction and improved air connectivity, and cost-efficiency

2 Background

2.1 Electric Aviation

In today's interconnected global society, aviation stands out as a prominent way of transportation, serving as one of the fastest ways to connect people and businesses across the globe.[13] Presently, airplanes predominantly depend on fossil fuels, contributing to climate change. Consequently, there is a growing demand for more sustainable aviation solutions. Recently, electric aircraft have emerged as one of the most promising innovations, offering significant benefits such as reducing greenhouse gas emissions and decreasing noise levels. [7] Moreover, electrification of traditional components of an aircraft is proven to reduce the carbon taxes and fuel cost, thus, further increasing the aircraft efficiency. [14]

All-electrified aircraft (AEA) and hybrid-electric aircraft (HEA) are two concepts within electrification. An AEA relies solely on batteries as a power source. Even though this is an efficient and sustainable concept the solutions face several challenges such as charging infrastructure and flight distance capacity. However, the HEA concept is an electric aircraft that relies on both battery and fuel, being a more flexible solution as they can operate on two power sources. Thus, having a larger distance capacity and requiring shorter recharging time.[7]

2.2 Swedish Initiative

Within the Swedish aviation industry, SAS, Swedavia, and RISE introduced the initiative Fossil-Free Aviation (Fossilfritt flyg) with the goal that all domestic flights should be fossil-free by 2030 and for all aircraft departing from Swedish airports to be fossil-free by 2045.[4] Due to the large geographical differences between Swedish regions, there is reliance on domestic aviation. [12] An effective electric aviation infrastructure could potentially enhance accessibility to smaller towns and rural areas. Thus, having a positive impact on regional development as electric aviation could enable transportation services from existing airports that currently lack significant commercial traffic. [9]

One example of the innovative advancement within the Swedish electric aviation industry is the ES-30, an electric aircraft manufactured by Heart Aerospace, with plans for its launch in 2030. The aircraft has a seating capacity for 30 passengers and a flight range of 200 km. Moreover, an ES-30 hybrid-electric solution could extend its flight range to 400 km and with a reduced passenger load of 25, the flight range would substantially increase to 800 km.[3]

2.3 Previous Research on Aviation Networks

The hub location problem has long been acknowledged within the field of operations research, transportation, geography, and network design. The problem aims to determine the optimal locations for hub facilities that manage the consolidated flow of, for example, goods or people, between origins and destinations.[5]

This field of research has seen significant growth in recent years, with a focus on addressing more extensive and complex problems that account for stochastic elements that address uncertainty and risk in network design and operation. Additionally, there is an increased emphasis on models that factor in both cost and service considerations, as well as dynamic models that account for changing demand and network conditions.[5]

Most aviation network design methods today are constructed around the base assumptions of H&S-models. While there is some variation, the assumptions relevant for this paper can be summarized as

- Consolidation of flow is economically desirable;
- The number of empty seats depends only on whether the flight is between two hubs or between a hub and a spoke;
- The cost of opening hubs should be accounted for in the model;
- The entirety of an origin-destination pair's flow will be accommodated through a single route;
- Rerouting flow through hubs is economically beneficial.

[5] [8] These assumptions heavily rely on the concept of economy of scale; in this context, letting the number of empty seats be a constant (with an intra-hub discount), which results in a model that will favor high-flow arcs. Strides have been made in making these models account for a varied fleet, for example, [11] extend the H&S model to include a variation in the reach and pricing of the air-crafts. While there is nothing fundamentally wrong with the assumptions of H&S, models that rely on them cannot account for a fleet with heterogeneous *capacities.*

We theorize that the low capacity of electric air-crafts might mean that low-demand legs like Gällivare-Luleå could become profitable to operate. That is: the aim is to explore the benefits of opening up low-flow arcs, something which runs counter to the underlying assumptions of H&S.

MILP and MCFN Therefore, we depart from the HS model and shift our focus to the utilization of Mixed Integer Linear Programming (MILP), particularly in the context of Multi-Commodity Flow Network (MCFN) problems. MILP is a suitable choice for this model, as it aligns seamlessly with scenarios where entire aircraft are considered as either fully utilized or not used, rendering them as integer variables. This provides us with the tools to charge full price for an operational aircraft, regardless of the number of passengers. For the problem formulation to make sense we must move away from the economy of scale in H&S, where often yearly flow is considered, and instead, we will consider something closer to daily flow. Additionally, hubs will no longer be considered beneficial and no specific cost for constructing hubs will be incurred. The difference in scale, and in fundamental assumptions, between the problems unfortunately make them hard to compare.

3 Mathematical Formulation

We begin with presenting the model by [8], which our model is based on. After which, our changes to the model is introduced, motivated and explained. In addition, some variations of or model is presented.

3.1 Base Model

Parameters and sets

$$
\begin{aligned}
J &= \text{set of airports (nodes); indexed with } i, j, \\
&\quad \textbf{and} \text{ set of commodities; indexed with } h \\
N &= \text{set of air crafts; indexed with } n \\
OD_{ij} &= OD_{ji} \text{ origin-destination pairs with demand, i.e., the number of passengers} \\
&\quad \text{who wish to travel from from node } i \text{ to node } j \text{ (assumed symmetric)} \\
D_{ij} &= D_{ji} \text{ Euclidean distance between } i \text{ and } j \\
C_n &= \text{cost per unit length of operation for aircraft of type } n \\
L_n &= \text{one time cost associated with operating plane } n \text{ (take-off/landing/etc)} \\
C_{ij}^n &= C_n \cdot D_{ij} + L_n = \text{ cost of operating aircraft } n \text{ on arc } (i, j) \\
K_n &= \text{max capacity of aircraft } n \\
R_n &= \text{reach (max flying distance) of aircraft } n
\end{aligned}
$$

Formulation of the problem Given the origin-destination demand of passengers, a set of aircrafts, and a set of airports, we want to construct a network - together with a routing policy - that satisfies the demand, while minimizing the operational cost. Like [8] we choose to model this as a Multi-Commodity Network Flow problem, with passengers and their desired destination as the commodities. An airport is called a node, and a pair of airports is called an arc. If there is a direct flight between two airports we say that the arc is open. The capacity of the arc will be dictated by which aircraft(s) are operating on the arc, and the cost of opening an arc will depend on which aircraft(s) are assigned to the arc.

Before stating the model of [8], we will begin by clarifying what we mean by commodities.

Commodities A passenger with final destination h is simply considered a commodity of type h. This can be a little confusing since the set of commodities and the set of nodes is a one-to-one map, that is: $h \in J$, and the use of h (as opposed to i or j) as an index is an attempt to mitigate this. The sources in the network simply correspond to the demand in an origin-destination pair, i.e., the number of commodities of type h that have their source i is the number of passengers who want to travel from i to $j = h$. Since $OD_{ii} = 0$ we write this as

$$(\text{source i})_h = OD_{ih}, \quad i \neq h \in J.$$

The total sink at node i is the inverse of the total amount of commodity type $h = i$ that exists within the network, i.e., the sum of passengers who want to travel *to* node i from any node $j \in J$, such that

$$(\text{sink i})_i = -\sum_{j \in J} OD_{ji}.$$

For simplicity the sources and sinks are combined into the (destination, commodity)-pairs W_i^h:

$$W_i^h = \begin{cases} OD_{ih} & \text{if } i \neq h \\ -\sum\limits_{j \in J} OD_{ji} & \text{if } i = h. \end{cases}$$

Original policy The all-stop policy proposed by [8], can be stated plainly as: If there is any flow on an arc, the arc must be operated by a number of planes with a combined capacity exceeding that flow. To accommodate this flow - any number of planes, of any type - can operate on a given arc. While the notation differs significantly from the original, we state the mathematical formulation of the problem as:

Let $f_{ij}^h \geq 0 \in \mathbb{R}^{\mathcal{A} \times J}$ be the flow of commodity h on arc (i, j) and let a_{ij}^n be an integer-valued decision variable s.t.

$$\begin{aligned} a_{ij}^n \geq 0 \in \mathbb{Z}^{\mathcal{A} \times N_{ij}} = {} & \text{the number of type } n \in N_{ij} \text{ air-crafts,} \\ & \text{that operate on arc } (i, j) \in \mathcal{A}, \end{aligned}$$

where

$$\mathcal{A} = \{(i,j) : i,j \in J : D_{ij} \leq \max_{n \in N_{ij}} (R_n)\},$$

is the set of arcs that can be operated by the fleet, and

$$N_{ij} = \{n \in N : R_n \geq D_{ij}\}$$

is the set of aircrafts that are feasible on arc (i,j). The optimization problem becomes:

$$
\begin{aligned}
\text{(OP)} \qquad \min \quad & \sum_{(i,j)\in\mathcal{A}} \sum_{n \in N_{ij}} C_{ij}^n a_{ij}^n && && \text{(1a)}\\
s.t. \quad & \sum_{j \in J_i} f_{ji}^h + W_i^h = \sum_{j \in J_i} f_{ij}^h, && h, i \in J && \text{(1b)}\\
& F_{ij} = \sum_{h \in J} f_{ij}^h, && (i,j) \in \mathcal{A}, && \text{(1c)}\\
& F_{ij} \leq \sum_{n \in N_{ij}} K_n a_{ij}^n, && (i,j) \in \mathcal{A}, && \text{(1d)}\\
& f_{ij}^h \geq 0 \in \mathbb{R}^{\mathcal{A} \times J}, && && \text{(1e)}\\
& a_{ij}^n \geq 0 \in \mathbb{Z}^{\mathcal{A} \times N_{ij}}, && && \text{(1f)}
\end{aligned}
$$

where J_i is the set of airports that are immanently reachable from i, that is:

$$J_i = \{j \in J : (i,j) \in \mathcal{A}\}.$$

Constraint 1b ensures conservation of flow. Constrain 1c is simply an assignment of total flow to make the other constraints more legible. Constraint 1d ensures that the flow on an arc is equal to or less than the capacity of that arc.

The conditional sets $\mathcal{A}$, N_{ij}, and J_i are computed as part of the pre-processing, in order to reduce the computational complexity of the problem. We note that while it is reasonable that some arcs cannot be operated, i.e., that

$$N_{ij} = \{\emptyset\} \quad \Leftrightarrow \quad (i,j) \notin \mathcal{A},$$

in order for the model to be feasible the pre-processing should include a step to ensure that $J_i \neq \{\emptyset\}$.

Unlike [8] we have instead opted for a policy where only one type of aircraft will service an open arc.

3.2 Our Model

Changes to the policy As well as instituting a policy where only one type of aircraft will service an open arc, we will be much more selective in how and when we allow for a multiple of air-crafts to be chosen; Only if the flow is high enough to require more than one aircraft - that is if the flow exceeds the maximum capacity of the highest capacity aircraft available - a multiple of *only* that specific aircraft is allowed to operate on the arc.

There are two reasons for this change. First, it reduces the complexity of the problem. This is expanded upon in Section 3.3. Further, and more importantly, we believe it is more true to how airlines operate; An open arc is most likely operated by one (general) type of aircraft, and for arcs with high enough flow, the largest airplane types would most likely be utilized.

The policy can be stated as:

$$\begin{aligned}
&\quad \text{if the total flow on arc } (i,j) \ \leq \max_{n \in N_{ij}} (K_n), \\
&\qquad \text{choose only one type of aircraft} \\
&\text{and} \\
&\quad \text{if the total flow on arc } (i,j) \ > \max_{n \in N_{ij}} (K_n), \\
&\qquad \text{choose any number of the highest capacity aircraft.}
\end{aligned}$$

Maximum capacity aircraft Since N_{ij} depend on the arc so - in general - does $\max\limits_{n \in N_{ij}} (K_n)$. In this paper however, N_{ij} depends only on the length of the arc (D_{ij}). Further, we assume throughout that the highest capacity aircraft is equivalent to the aircraft with the longest reach, i.e.,

$$\max_{n \in N_{ij}} (K_n) = \max_{n \in N} (K_n).$$

For this reason, as well as to make the notation cleaner, we will denote this aircraft type as m (as opposed to m_{ij}), that is

$$\max_{n \in N_{ij}} (K_n) = K_m.$$

It is not hard to imagine scenarios where m does depend on the arc, especially considering electric aviation, where reach is only one limitation; Some smaller airports might not have landing strips long enough to accommodate traditional aircrafts, while others might lack electric charging stations. For this reason, we want to make it clear that the model does account for this, even though we have opted not to include the dependence on arc *in the notation* going forward.

In addition, our policy also includes that all aircraft assignments should be symmetric over $\mathcal{A}$.

Mathematical formulation In order to model this policy we need to make some changes to existing - as well as introduce additional - variables. First, we need to be able to distinguish between an aircraft type that can only be used once and *the same aircraft* that can be used multiple times on an arc. This is a boring notation issue, and the solution is simply to choose the index m such that

m corresponds to an aircraft in N_{ij}, while still being distinct so that $m \notin N_{ij}$. To simplify notation, we also (re-)define the sets N_{ij} as the sets which contain aircrafts that can only be used once. The decision variables corresponding to aircrafts in N_{ij} will be binary, as opposed to integer-valued. The set of all aircrafts is then

$$N_{ij}^m = N_{ij} \cup \{m\}$$

In addition to this we also define a variable for if the arc is closed:

$$a_{ij}^0 = \begin{cases} 1 & \text{if no plane operates on arc } (i,j) \\ 0 & \text{else,} \end{cases}$$

as well as an indicator variable s.t.

$$b_{ij} = \begin{cases} 1 & \text{if } a_{ij}^m \geq 0 \\ 0 & \text{if } a_{ij}^m = 0. \end{cases}$$

The added and/or changed variables are

$$\begin{aligned} a_{ij}^n \in \{0,1\}^{\mathcal{A} \times N_{ij}} &= \text{ assign one aircraft of type } n \text{ to operate on arc } (i,j) \\ a_{ij}^0 \in \{0,1\}^{\mathcal{A}} &= \text{ assign no aircraft to operate on arc } (i,j) \\ 0 \leq a_{ij}^m < M \in \mathbb{Z}^{\mathcal{A}} &= \text{ assign an integer number of aircraft } m \text{ to operate on arc } (i,j). \\ b_{ij} \in \{0,1\}^{\mathcal{A}} &= \text{ indicator variable as to whether } a_{ij}^m \geq 1 \text{ or } = 0, \end{aligned}$$

where M is a large scalar s.t.

$$M > \frac{\text{total demand}}{K_m}.$$

That is, the maximum number of needed aircrafts is limited by the total flow and the maximum capacity.[3]

[3] If m depends on (i,j), M would have to be defined accordingly.

We state the full problem:

$$
\begin{aligned}
\text{(P)} \qquad & \min \quad && \sum_{(i,j)\in\mathcal{A}} \sum_{n\in N_{ij}^m} C_{ij}^n a_{ij}^n && && \text{(2a)}\\
& s.t. && \sum_{j\in J_i} f_{ji}^h + W_i^h = \sum_{j\in J_i} f_{ij}^h, && h, i \in J && \text{(2b)}\\
& && F_{ij} = \sum_{h\in J} f_{ij}^h, && (i,j)\in\mathcal{A}, && \text{(2c)}\\
& && F_{ij} \le \sum_{n\in N_{ij}^m} K_n a_{ij}^n, && (i,j)\in\mathcal{A}, && \text{(2d)}\\
& && a_{ij}^0 + \sum_{n\in N_{ij}} a_{ij}^n + b_{ij} = 1, && (i,j)\in\mathcal{A} && \text{(2e)}\\
& && M\cdot b_{ij} \ge a_{ij}^m, && (i,j)\in\mathcal{A} && \text{(2f)}\\
& && M\cdot(1-b_{ij}) > -a_{ij}^m, && (i,j)\in\mathcal{A} && \text{(2g)}\\
& && a_{ij}^n = a_{ji}^n, && (i,j)\in\mathcal{A}, n\in N_{ij} && \text{(2h)}\\
& && f_{ij}^h \ge 0 \in \mathbb{R}^{\mathcal{A}\times J}, && && \text{(2i)}\\
& && a_{ij}^n \in \{0,1\}^{\mathcal{A}\times N_{ij}} && && \text{(2j)}\\
& && a_{ij}^0 \in \{0,1\}^{\mathcal{A}} && && \text{(2k)}\\
& && a_{ij}^m \ge 0 \in \mathbb{Z}^{\mathcal{A}} && && \text{(2l)}\\
& && b_{ij} \in \{0,1\}^{\mathcal{A}}. && && \text{(2m)}
\end{aligned}
$$

The assignment of indicator variable b_{ij} is guaranteed by constraints 2f and 2g. Constraint 2e then says that for an arc we can choose either: no aircraft, one aircraft *or* a multiple of aircraft with capacity K_m.

In this formulation, we do **not** demand that

$$
b_{ij} = \begin{cases} 1 & \text{if the flow on } (i,j) \text{ exceeds the maximum capacity } K_m, \\ 0 & \text{else,} \end{cases}
$$

which, technically, is part of our policy. Rather the cost of choosing multiple planes, as included in the objective function, can be considered discouragement enough. This, however, might not always be the case. For further discussions on this, see Section 3.3.

Symmetry Constraint 2h means that the choice of aircraft on arcs has to be symmetrical. Not only that, its inclusion also means that there is no guaranteed feasible solution if the demand is non-symmetric ($OD_{ij} \neq OD_{ji}$). So by including this demand, we limit the application of the model, but with good reason. Symmetric demand is commonly assumed in aviation network design since most travel consists of round trips, so there is not really much loss of generality. And when constraint 2h is included, a solution to (P) is also a solution to the *fleet* *assignment problem.* Additionally, the number of decision a-variables is effectively halved by the constraint.

3.3 Variations on the Model

We can pretty easily see a downside of this formulation. Let the demand between i and j exactly equal the maximum capacity K_m. Further, say the solution to the problem includes that $a_{ij}^m = 1$. Simply upping the demand by one on (i, j) doubles the price of the arc. This could radically change the optimal solution. It also has little root in reality; Airlines do not guarantee seating, demand is not fixed, etc. There are different ways to handle this, two of which we will briefly cover. Both methods require that

$$b_{ij} = \begin{cases} 1 & \text{if the flow on } (i,j) \text{ exceeds the maximum capacity } K_m, \\ 0 & \text{else,} \end{cases}$$

which means we need to include additional constraints

$$M' \cdot b_{ij} \geq F_{ij} - K_m, \qquad (i,j) \in \mathcal{A} \tag{2n}$$

$$M' \cdot (1 - b_{ij}) > K_m - F_{ij}, \qquad (i,j) \in \mathcal{A}, \tag{2o}$$

where M' is the total demand.

Relaxation of the problem One way to handle this is by saying that if the flow on an arc exceeds the maximum capacity K_m then the cost for each additional passenger is continuous. The only change in formulation is relaxing the demand that a_{ij}^m be integer-valued, i.e., change constraint 2l to

$$a_{ij}^m \geq 0 \in \mathbb{R}^{\mathcal{A}} \tag{2l}$$

As soon as more flow is routed through an arc than K_m there is no longer any penalty for unused seats. There is precedence for the assumption that consolidation of flow can equal a reduction in empty seats, and generally a reduction of cost - it is after all one of the base assumptions of many Hub & Spokes-models. However, simply routing more than, say, 100 passengers through an arc might not be significant enough to justify such cost reduction. Another way to handle this could instead be to change the capacity - and the corresponding cost - of m.

Changing $\boldsymbol{m}$ Given the largest plane, which can only be operated *once* on an arc $m_{once} = m_1 \in N_{ij}$, with cost $C_{ij}^{m_1}$ and capacity K_{m_1}. Until now we have defined the plane m as a plane we can operate *more than once* on an arc, with parameters $C_{ij}^m = C_{ij}^{m_1}$ and $K_m = K_{m_1}$. With the inclusion of constraints 2o and 2n this is no longer necessary. For example we can let $C_{ij}^m = \frac{1}{5} C_{ij}^{m_1}$ and $K_m = \frac{1}{5} K_{m_1}$. Now the case of adding one more passenger on the arc would lead to a 20 % increase in cost, as opposed to a 100 % increase. The cost reduction is now not so immediate and drastic as in the fully relaxed problem, while still making the solution somewhat less sensitive to minor changes in demand.

Due to limitations in scope, we will omit these variations from the results.

Time complexity The computational complexity of the problem imposes some limitations on what we can hope to achieve with the model. Additionally, it is part of the motivation for the changes made to [8]. For this reason, a short analysis of the computational complexity is included here, as opposed to as a result in section 5

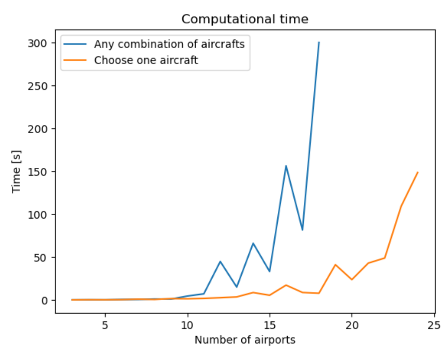

Fig. 1: Computational time with an increasing number of airports - i.e.., increasing the size of J, and fixed $n = 5$.

Mixed Integer Linear Programming problems are computationally complex since it is classified as NP-complete. The time complexity for a MILP problem is typical exponential $O(2^n)$ where n is the number of variables or constraints used and thus, we expect the computational time to increase exponentially as the number of variables increases. This can be seen in Figure 1, where we plot the computational time as a function of the size of the network (size of J). The plot shows the computational time for both the original problem (all a_{ij}^n integer-valued), as well as the computational time for our model.

It might not be instantly clear that allowing for only one aircraft to operate on each arc reduces the computational complexity of the problem. Especially since that means introducing additional variables such as: $b_{ij} \in \{0,1\}^{\mathcal{A}}$, while also adding multiple constraints. But the benefit of replacing the majority of the integer-valued decision variables with binary variables - only a_{ij}^m remain integer valued - does, as we can see in Figure 1, more than makes up for this.

Due to this computational complexity and time constraints, the choice was made to only solve for airports north of - and including - the Stockholm region.

4 Data

Aviation demand data One way to test the model would be to test it on available benchmark data sets, such as the CAB data used in the paper by Jaillet et al. [8] In that particular study, the data set describes the air passenger traffic between 39 cities in the United States. However, there is a large discrepancy between the geographical conditions in the U.S. and in Sweden. More specifically, the traveling distances in the U.S. are generally significantly longer than the ones in Sweden. For instance, the route from Los Angeles to New York is approximately 3,900 km, which is almost twice as long as the entire Sweden (approximately 2,100 km). Thus, in order to more accurately evaluate the performance of our model in a Sweden context, we need data on the origin-destination demand situation in Sweden. To get this information, a data set was provided by our project supervisor, simulating an imaginary future demand scenario in Sweden, including routes between 40 airports across the entire country. However, this data set only contained point-to-point data. In the lack of better data sources, this was used as origin-destination data to test the model. Additionally, since the granularity of the demand data was only on a monthly level, we proceeded to transform the data to daily demand. To do this, we assumed that the demand was uniformly distributed across all months and that the average number of days in a month was 30. However, after the mentioned transformation of the data, a large part of the arcs had very a small demand (close to 0). To make the data more interesting and better resemble a real scenario, these data points were increased with a random factor between 0 and 10. This was also done for the arcs with 0 demand, as that would be highly uninteresting for the testing of the model. Additionally, it can also be argued that these adjustments will make the data better resemble an origin-destination structure, as the demand on the current high-flow arcs (such as to/from Arlanda) will be more distributed among the other destinations in that case.

Lastly, the destinations in the demand data set could all be linked to their respective airports, which in turn could be linked to precise coordinates. Consequently, these coordinates were used to get the Euclidean distances between the airports.

Aircraft data and assumptions In order to compare the different aircrafts used in this study, data describing the costs for each type of aircraft is needed. Apart from some constant cost for landing, the main cost driver for each aircraft is assumed to be the distance traveled. In other words, as the cost should be distance-based, the cost of interest is the operating cost during flight.

As mentioned previously, the chosen electric aircraft for this study is the ES-30, produced by Heart Aerospace, with a 30 pax capacity. According to their website, the ES-30 has a similar operating cost to a 50-seat turboprop [3]. Additionally, the aircraft has zero emissions for distances below 200 km (using the fully electric option), and 50% less emissions for longer routes, compared to a 50-seat turboprop. Thus, to get an estimate of the operating costs of such an aircraft, data was gathered from AOPA's website, where different types of aircraft are compared in terms of capacities, ranges, and costs. [1] However, since we are interested in the operating costs per km and the variable operating costs on the website are on an hourly basis, the data needed to be transformed to be compared to the other aircrafts. This was done by dividing the hourly operating cost with its cruising speed, effectively yielding a distance-based measure of the operating costs instead.

For the conventional aircraft, the CRJ900 is chosen, which is a common aircraft for domestic flights in Sweden. Compared to the ES-30, the CRJ900 has a larger capacity of 90 pax, a longer range of 2,100 km, as well as a higher cruising speed [2].

During the initial research on the aircrafts, following the indications on Heart Aerospace's website, the operating costs were found to be higher for the electric aircrafts than for the conventional aircrafts. This may be due to a discrepancy in the different sources' assumptions and included elements in the operating costs. However, this cost structure defeats the purpose of the cost benefits that electric aviation brings. Thus, in order to make the testing of the model more feasible, the costs used are assumptions of how a potential future scenario might look like, similar to the demand data. This way, we can test the model under the conditions that electric aviation offers significant cost benefits due to lower variable costs, although having a shorter range and lower pax capacity (these factors are kept from the initial market research on the aircrafts). The aircraft data will be presented in more detail in Section 5.3.

5 Computational Results

5.1 Test Network

A network including four nodes was initially constructed to rigorously evaluate the model's performance across various parameter settings, with the primary objective of assessing its accuracy and logical coherence.

The initial test was performed with the following data

	point0	point1	point2	point3
point0	0	0	0	5
point1	0	0	0	5
point2	0	0	0	0
point3	5	5	0	0

Table 1: Origin-destination demand for the test network

The origin-destination symmetric matrix is given by Table 1 and Table 2 shows the parameters of two distinct aircraft options. The first aircraft, *plane1*,

	capacity	cost per km	max distance	landing cost
plane1	5	2	1.5	2
plane2	10	3	4	2

Table 2: Air fleet parameters of the test network

has the capacity sufficient to meet the demand given by the origin-destination matrix and has a flight range of 1.5, enabling it to reach the nearest node within the given network.The second aircraft, *plane2*, boasts a greater capacity, higher operational costs, and an extended flight distance. The distances between the nodes in the test network can be identified from the axes of the below plots. Where, *point0,point1* to *point2* is $\sqrt{2} \approx 1.4$, *point2* to *point3* is 1, *point0* to *point1* is 2 and *point0,point1* to *point3* is $\sqrt{5} \approx 2.2$

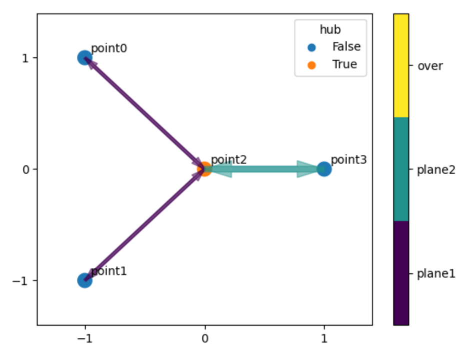

Fig. 2: base solution

The results from the test data are visualized in Figures 2 to 4, illustrating three separate scenarios. Firstly, Figure 2 shows the base solution, using the data stated in Table 1 and Table 2. The presented solution shows that *plane1* is primarily utilized to consolidate passengers from their respective origins, channeling them to *point2*, acting as a hub. Subsequently, *plane2*, with higher capacity, transports all passengers to their final destination, *point3*.

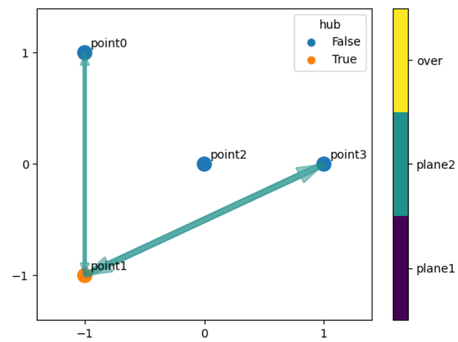

Fig. 3: increase in landing cost

The solution visualized in Figure 3 illustrates the impact of an increased landing cost from 2 to 5. Consequently, the revised solution suggests the utilization of *plane2* for the route between *point0* and *point1*. At this node, *plane2* is then employed to collect the remaining passengers before continuing to *point3*, all within the same aircraft.

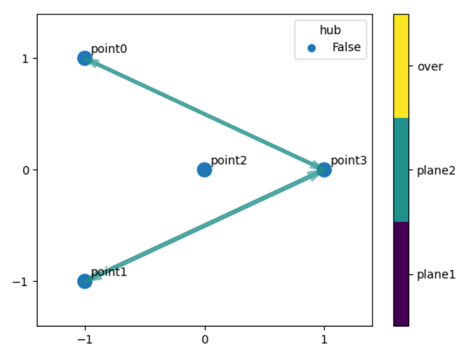

Fig. 4: increase in passengers

Finally, Figure 4 shows the solution of the scenario where the demand of the passengers, specifically those wanting to travel from *point0* to *point3*, increases. The illustration shows that the optimal network solution calls for the utilization of two aircraft of type *plane2*. These aircrafts both follow direct routes to the destination: one departs from *point0* to reach *point3*, while the other departs from *point1* and arrives at *point3*.

5.2 Final Network

	capacity	cost per km	max distance	landing cost
AEA	30	15	200	100
HEA	30	20	400	100
Conventional	90	45	2100	500

Table 3: final network's parameters

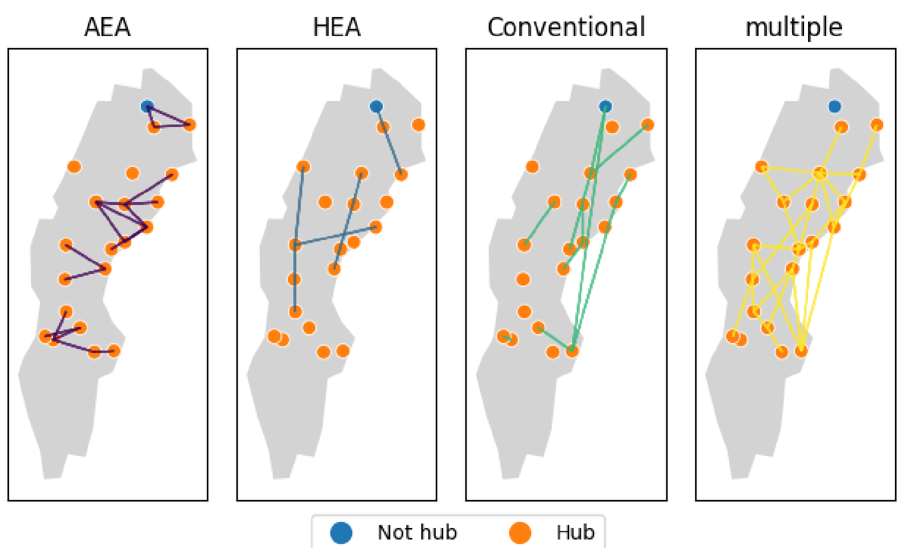

Fig. 5: Optimal solution with one plot per plane

Table 3 Shows the parameters used to create a fleet assignment model with the actual data, which is explained in detail in section 3.1.

The optimal solution found from the given data is presented in the four plots in Figure 5, where the four different plots represent the legs flown by the three different types of planes. The plot called *multiple* indicates the legs where the demand was larger than the capacity of the biggest plane (conventional) and thus more than one plane was needed to fly that leg. The results showed that 18 of the arcs was flown using the AEA, 5 arcs was flown using the HEA and lastely the conventional plane was flown on 40 of the networks arcs.

The MIP problems in Algorithm are solved by Gurobi [6], which is the state-of-art MIP solver. The computations were executed via Gurobi 10.0.0 under Python 3.81 on a HP ENVY x360 (2018) notebook with an Intel Core i5 1,6 GHz Quad-core and 8 GB of RAM.

6 Discussion

6.1 Model Evaluation

As previously discussed, the model presented in this paper has been developed to accommodate the emergence of electric aviation technologies. This new model explores the feasibility and economic benefits of opening low-flow arcs as electric aviation incurs significantly lower costs combined with the emerging access to smaller planes.

In contrast to the conventional H&S's assumption, where the optimal route typically traverses a central hub to benefit from economies of scale through consolidated flow, the results presented in this paper diverge from the concept of consolidated flow. Instead, they advocate for a point-to-point network without distinct hubs, such as the current Arlanda setup.

While a point-to-point network appears promising in the context of electric aviation and the enhancement of regional connectivity, it is important to acknowledge that the proposed model sacrifices the benefits of economies of scale associated with hub operations. Furthermore, the proposed model disregards the aspect of time travel. Hence, it allows the possibility of several layovers compared to the traditional H&S model which typically only allows one layover when transiting through a hub. Consequently, certain flight routes may prove impractical in practice due to their time-consuming routing.

Furthermore, as outlined in Section 3.3, the model exhibits a notable degree of sensitivity when demand marginally exceeds an aircraft's maximum capacity. The substantial escalation in costs concerning the demand shift does not accurately mirror real-world dynamics. Consequently, this heightened sensitivity poses a considerable obstacle as demand cannot be presumed to remain constant in practical scenarios. Therefore, it is imperative to recognize and address this challenge for future research, necessitating the adoption of the methodologies expounded in Section 3.3.

6.2 Analysis of Result

Analysis of the results from the test network The results of the test data provide valuable insight into the impact of various factors on the network design. Notably, costs and shifting demand emerge as pivotal variables influencing the optimal flight routes and choice of aircraft. Especially, fig. 3 visualizes how an increased landing cost could change the initial network design presented in fig. 2. The increase in cost changed both the aircraft type and optimal flight paths. In this case, the utilization of *plane1*, with its relatively lower capacity becomes less economically viable for consolidating the passengers at a hub. The requirement of three such airplanes in this scenario incurs a higher cost, making it less cost-effective. Consequently, the revised solution with only two planes offers greater efficiency and cost-effectiveness. It is worth emphasizing that the cost is currently presented in monetary terms. In reality, a comprehensive cost assessment would encompass additional factors, including time travel consideration, infrastructural development prerequisites, and emissions.

Furthermore, fig. 4 visualizes how demand fluctuations significantly influence network optimization. In this scenario, the conventional strategies of consolidating passengers at *point2* and initially departing from *point0* to pick up additional passengers at *point1*, are no longer the preferred choices. This change is primarily due to the capacity limitations of *plane1*, which can not accommodate the increased demand of passengers wanting to reach *point3*.

Analysis of the results from the Final Network The result from the final network showed that the majority of flights were flown using the larger plane, due to the fact that that plane can take a higher number of passengers and travel a longer distance. Specifically, the results demonstrate the allocation of the AEA to shorter flight routes. Thereby, expanding and improving the connectivity of the aviation network. Furthermore, the optimal solution highlights a limited utilization of the HEA. This result is primarily due to the similar passenger capacity of HEA and AEA. However, given that the AEA is more cost-effective, it generally outperforms the HEA in most scenarios despite the fact that HEA has a longer flight range.

This report and the associated model have been focusing on the integration of new technology, resulting in the inclusion of one single conventional airplane. However, it is crucial to acknowledge the existence of larger aircraft options that could be deployed to manage the flight legs presented in the *multiple* plot. Leveraging these larger planes could offer enhanced efficiency and cost-reduction advantages when operating multiple aircraft types simultaneously.

6.3 Data and Computational Limitations

Data limitations One critical limitation of the demand data is that it only reflects point-to-point data and not origin-destination data. In other words, the data does not take into account that the demand between two cities can be a part of a two-leg trip, and that the demand to Arlanda includes a large portion of layover flights. Consequently, this entails that the demand going to/from Arlanda is higher in the current data set, than it would be if it were to reflect the origin-destination demand data, as per the point-to-point nature of the data.

Another limitation is that the demand data is "imaginary" and represents a hypothetical future scenario. Furthermore, it is not stated how this data was generated or gathered, giving the data an even more speculative nature. Thus, we can't rely on the data to accurately reflect the real aviation demand in Sweden.

In terms of aircraft data and costs, there is quite scarce information about the electric aircrafts, especially in terms of operating costs. When researching the costs associated with electric aviation, it was difficult to find correct and concise. For instance, as mentioned previously, the operating costs of the ES-30 is "similar to 50-seats turboprop", indicating that there the exact cost might still be unknown and merely estimated. [3]

However, the aim of this paper is not to determine a comprehensive and accurate future network flow. Instead, the main objective is to develop and test a model that accommodates the emergence of electric aviation technologies and other additional parameters to consider in the modern aviation landscape, challenging the current hub-based network flow.

6.4 Practical Implication

Passenger preference implications The model's primary challenge is its reliance on static demand. Emerging electric transportation technologies and new sustainable travel options will likely change transportation preferences as we know them today. The increasing demand for sustainable travel and electric aviation makes the proposed model increasingly pertinent. Nevertheless, it is crucial to recognize the dimension of travel time. While the model's routing network may appear optimal based on emerging electric aviation technologies, their practicality for passengers remains uncertain. Passenger preferences evolve rapidly, thus affecting the attractiveness of the implementation of a new network design. Notably, this fluctuation makes the orgin-destination data, used in this paper even less reliable, and as such - it might be even more detrimental with a model so sensitive to changes in demand.

Furthermore, changes in the electric transportation landscape and infrastructure development may introduce competitive alternatives for travel, particularly for short-distance routes. Consequently, future research must determine how this will affect low-flow and high-flow routes and ultimately the implications on the model.

Infrastructural Implications The proposed shift from the conventional H&S network to a point-to-point network imposes new infrastructure requirements. Firstly, transitioning to a point-to-point network introduces greater operational complexity as numerous airports become viable for commercial flights. This complexity necessitates a revised strategy for flight coordination and scheduling.

Moreover, integrating electric aviation demands significant alterations to airport infrastructure. Airports must adapt their facilities to accommodate electric aircraft, including the installation of charging stations and energy storage solutions. These challenges require collaborative efforts involving stakeholders in the electric aviation industry, including energy providers and infrastructure developers, to facilitate the transition toward a more electric-based aviation sector. Traditional H&S does take the cost of constructing hubs into consideration, something that could be of even more importance to incorporate when future modifications of the model as a complete re-haul of current infrastructure would be costly.

7 Conclusion and Outlook

The changing landscape of aviation might require a new standard in aviation network design. There is reason to believe new models should be able to take a radically diverse air-fleet into consideration. We have proposed a model that does account for aircrafts with varied capacities, flight range, and cost-profiles. There is of course a trade-off. Consolidation of flow, which our model does not tend towards, could remain desirable. Further, the integer nature of the model makes it sensitive to minor changes in demand. This is not a desirable quality, especially if the model is to be used in long-term planning of a country's aviation network.

Future research might look to combine H&S with this more granular MCNF-formulation. One way to do this could be by designing a base network using H&S and later looking at opening up some specific arcs using MCNF. One could also look into modifications of our model, such as allowing for greater discounts with increased flow (as mentioned in Section 3.3). While other aspects from H&S could be incorporated, such as the cost of building hubs, any additional aspect could significantly add to the computational complexity of the problem.

We have also looked at what type of data will be necessary, in order to make this type of analysis. Moreover, it can be concluded that that there is currently a gap between the data we have and the data we need to make an accurate assessment of the impact that electric aviation will have on the network flow. Most predominantly, due to the scarcity of aircraft data available today. This is not that surprising, as electric aviation is still in its infancy and development phase. However, due to the fast advancements in that field today, we can safely assume that the required data will be available in the short future when electric aviation gets more established on the market. Additionally, as mentioned previously, a more reliable data source of the current origin-destination data is needed to understand and model the Swedish aviation market.

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