A two-stage optimization approach for selecting electric-flight airports

Frederic Kroner[1,2,4] Imke Joormann[1,2]
Andreas M. Tillmann[3]

[1] Cluster of Excellence SE^2A—Sustainable and Energy-Efficient Aviation, Technische Universität Braunschweig, 38106 Braunschweig, Germany
[2] Institute of Automotive Management and Industrial Production, Technische Universität Braunschweig, Mühlenpfordtstr. 23, 38106 Braunschweig, Germany
[3] Institute of Mathematics, Clausthal University of Technology, Germany
[4] Corresponding author: frederic.kroner@tu-braunschweig.de

The decarbonization of short-haul air transport has gained increasing attention, with electric aircraft emerging as a promising alternative to conventional short-haul aviation. However, given the substantial investment anticipated for the necessary infrastructure, a strategic and globally coordinated selection of airports is imperative. The aim of this paper is to address this problem and determine the best possible selection of airports within a given network. To this end, we develop a two-stage mixed-integer optimization model that incorporates airline decision-making in response to infrastructure deployment. The first stage determines which airports to electrify under budget and technical constraints, while the second stage models airline routing choices based on cost-minimization. The problem is reduced to a single-stage mixed-integer programming framework and solved using a cutting-plane procedure together with a column generation approach. We tested our algorithm in two infrastructure expansion scenarios in Germany. For each scenario, we consider the results for electric aircraft with ranges of 300 km and 1480 km. The results indicate that the differences in emission savings between the two range scenarios are marginal. Simultaneously, the optimal solutions demonstrate robustness to fluctuations in kerosene and electricity prices. Additionally, based on the given assumptions and parameters, using routes that are partly operated by electric and conventional aircraft does not appear to be economically viable for short-haul air traffic from an airline's perspective.

1. Introduction

Aviation is a key enabler of global connectivity, facilitating the movement of people and goods over long distances. It plays a vital role in international trade, tourism and global collaboration. Concurrently, the industry is also a major contributor to climate change: Aviation is responsible for around 2.5 % European Union Aviation Safety Agency [11] of global carbon dioxide (CO_2) emissions, while within the European Union (EU) the share is roughly 3.8 % to 4 % [4]. CO_2, produced by the combustion of aviation fuel, is a major greenhouse gas that contributes to global warming [22]. In addition, jet fuel combustion at high altitudes produces water vapor, which forms condensation trails that contribute to cloud formation. These clouds trap heat by reflecting solar radiation back to the Earth's surface, further increasing the warming effect [32].

Therefore, reducing the environmental impact of the air transportation sector represents a significant contemporary challenge. In response, the Advisory Council for Aeronautics Research in Europe (ACARE) launched Flightpath 2050 in 2011 [10]. This initiative aims to reduce CO_2 emissions from European aviation by 75% compared to year-2000 levels by 2050. As achieving this target depends on advances in technology, sustainable fuels, and operational improvements, recent years have seen substantial research efforts aimed at enabling a more sustainable air transport system. A significant part of this is dedicated to research in the field of electric aviation. Electric aircraft offer several advantages: In addition to lower operating costs [2] and significantly quieter operation [31], their most crucial advantage in terms of sustainability is the absence of direct CO_2 emissions during operation [2]. However, their main limitations lie in their restricted range and seating capacity, which currently constrain their applicability to short-haul routes, which refers to flights with a distance of less than 1500 km [40]. Nevertheless, in the near future—at least for short-haul flights—electric aircraft could become a viable option offering a more sustainable alternative to traditional aviation [1].

One of the most notable electric aircraft is the Eviation Alice, developed by the company Eviation. Its range is approximately 460 km, depending on the configuration specifics of the aircraft such as seating capacity and fully electric versus hybrid propulsion [12]. Another notable example is the ES-30, developed by the company Heart Aerospace with an expected operation range of 200 km to 800 km [16].

A key indicator for the rising popularity of electric aircraft is the growing interest from airlines. Several companies, including UrbainLink Air Mobility and Mesa Airlines, have announced their plans to add these aircraft to their fleets [28, 38]. In addition, Norway recently became the first country to declare the goal of making all short-haul flights purely electric, beginning in 2040 [8].

However, the successful future integration of electric aircraft requires overcoming several challenges. In addition to the mentioned technological limits, there are also considerable planning-related issues that must be resolved: At the airport level, infrastructure will need to be reorganized and expanded to meet the growing demand for electricity [33]. Meanwhile, on a global scale, it is important to determine where electric aircraft should be deployed and how to design an efficient charging network to support their integration. This requires significant investment in infrastructure.

Thus, the problem we focus on is to make the best use of a given budget to develop the infrastructure at various airports, enabling the use of electric aircraft so that the resulting emissions are minimized. Due to their limited range and seat capacity, electric aircraft are better suited for direct short-haul connections than traditional hub-and-spoke networks [5]. A shift towards decentralized route structures is therefore essential to fully realize their operational and environmental benefits. Hence, instead of predefined flight legs that must be served, we consider passenger demand for each airport pair, i.e., so-called origin-destination demand, representing the number of passengers to be transported between two respective locations. This allows any route within the network to be selected, thereby facilitating the optimal use of electric aircraft.

In the process, it is crucial to account for the fact that airlines independently decide which routes to offer and how to utilize any infrastructure expansions–their objective is to minimize their own operating costs.

This leads to a two-stage formulation: in the first stage, the leader determines infrastructure expansion to minimize emissions; in the second stage, the follower selects the most cost-efficient routes based on the given infrastructure, which is modeled as a multi-commodity flow problem. Within the bilevel optimization problem, the multi-commodity flows are modeled using a path-based formulation. To efficiently handle the exponential number of path variables, we employ a column generation approach [6]. Moreover, we introduce a set of cutting planes in order to reformulate the problem as a single-stage mixed-integer program. For the resulting solution approach, special attention has to be given to correctly combining the column with the cut generation. The source code and data is available at [18].

Overall, the present paper makes the following contributions:

(i) We propose a two-stage optimization model designed to support the selection of airports for expansion of the infrastructure to accommodate electric aircraft. The first stage captures the strategic decisions on airport infrastructure investment for electric aircraft operations by framing airport selection as a facility location problem. The second stage approximates the operational decisions of airlines regarding cost-efficient routing in the network established by the first-stage decisions, incorporating origin-destination demand between airport pairs by means of a multi-commodity flow formulation.

(ii) We develop a tailored solution methodology designed to efficiently address representative instances of the proposed bilevel optimization model, combining advanced decomposition techniques with problem-specific enhancements.

(iii) We demonstrate the benefits and practical insights of the proposed modeling approach using a case study inspired by real-world data focused on short-haul air traffic in Germany. In this context, we illustrate how the model can support decision-making by evaluating the impact of different budget levels for infrastructure expansion.

The remainder of the paper is structured as follows: After discussing relevant prior works in Section 2, we present the formulation of the proposed optimization model along with the corresponding solution methodology in Section 3. Section 4 reports the results of computational experiments and the application of the model to a real-world case study, respectively. Finally, Section 5 concludes the paper by summarizing key findings and outlining directions for future research.

2. Related Work

Studies have demonstrated that transitioning to electric aviation holds considerable potential for contributing to the achievement of the aforementioned emission targets [15, 42]. Much of the literature published to date—most within the last few years—deals with the technological aspects of electric aircraft in the fields of aircraft design and propulsion systems. This includes research on propulsion architectures, energy storage solutions, aerodynamics and power management. A comprehensive overview is provided by Madonna et al. [24].

Different challenges arise at the level of operational and infrastructure planning, respectively. These include the planning and development of infrastructure at a single airport as well as the design of a global charging network. Justin et al. [19] address peak power consumption and electricity costs by optimizing charging schedules based on an existing flight plan. In a first step, they determine the permissible combinations of charging stations and quantities of exchangeable batteries required to execute the flight plan. These configurations are then utilized to optimize the charging schedule under two distinct strategies, one aiming to enhance energy efficiency and the other to reduce operational costs. The approach by van Oosterom and Mitici [37] develops a recourse model to optimize the charging infrastructure for a given airport network, also utilizing a battery swapping system. Their model aims to minimize infrastructure acquisition costs (charging capacity and batteries) as well as operating costs (electricity expenses and flight delays due to battery charging). The model is tested on a flight network consisting of 7 hubs and 36 airports in Norway, using a given flight schedule and the existing configuration of the Eviation Alice electric aircraft. The work of Trainelli et al. [36] pursues a similar research direction, introducing the ARES optimization model, which determines for a given flight schedule the optimal sizing of future infrastructure to support electric aircraft operations by minimizing the combined total cost of, in particular, electricity consumption, battery acquisition, and charging equipment.

In further work on infrastructure planning, Kinene et al. [20] focus on the global planning of infrastructure development. They introduce the Electric Aircraft Charging Network for Regional Routes (EACN-REG) framework and formulate a one-stage optimization model as a location problem that seeks to maximize regional connectivity while minimizing the number of charging stations in the network. Rather than designing the network to meet specific passenger demand, their approach focuses on identifying origin-destination pairs that are technically servicable with respect to aircraft range and charging constraints in order to cover the maximum possible population by the resulting network.

At the modeling level, our problem consists of a facility location problem and a multi-commodity flow problem. Individually, both are well-known and extensively considered problems. Introductions can be found in Owen and Daskin [27] and Salimifard and Bigharaz [30], respectively.

The joint consideration of facility location and flow optimization frequently arises in transportation network design, and our problem therefore bears similarities to several variants discussed in the literature. As early as 1984, Magnanti and Wong [25] introduced a foundational modeling framework, widely recognized as the uncapacitated fixed-charge network design problem, to which various applications in this area can be traced back. It consists of a discrete choice variable and a part that models the flow decisions. This type of problem often occurs as a bilevel problem, where the upper-level represents the network design decisions made by planners or policymakers responsible for expanding and improving transportation infrastructure, and the lower-level captures traveler behavior, specifically travelers' decisions regarding whether to travel and their choices of mode and route. For example, Liu and Chen [23] deal with the Mixed Transportation Network Design Problem. In their formulation, the upper level seeks to optimize overall network performance by deciding on both the expansion of existing links and the addition of new candidate links, while the lower level models how travelers distribute across the network based on predicted travel times.

To address the computational challenges of mixed-integer bilevel programs (MIBLPs), several exact solution techniques have been developed in the literature. One common approach is single-level reformulation, where the bilevel structure is converted into a single-level problem using the Karush-Kuhn-Tucker conditions or strong duality. For instance, Zeng and An [41] propose a reformulation-based method combined with decomposition to solve MIBLPs. Another widely used strategy is branch-and-bound or branch-and-cut, which systematically explores the solution space while integrating valid inequalities to tighten the formulation. This is exemplified in [34], where the authors implement the branch-and-cut solver MibS capable of solving closed-form mixed integer bilevel problems with discrete decisions at both levels .

A comprehensive overview of those problems, specifically in the context of urban transport network design, is provided by Farahani et al. [13], who present different problem variants and methodological approaches found in the literature. For general bilevel problems [21] provides a useful overview.

3. Optimization Model and Solution Approach

We consider an undirected multigraph $G = (V, E)$. Let V represent the airports, and E the connections between them, differentiated by aircraft type. Let $\mathcal{F} = \{1, \ldots, F\}$ be the set of different aircraft types. We denote by E^e the set of edges that are associated with electric aircraft. In the following, we refer to the edges E^e as electric edges, and to the edges $E \setminus E^e$ as conventional edges. For each pair of nodes (v, w) with $i, j \in V, i \neq j$, let an undirected origin-destination (OD) passenger demand d_{vw} be given.

For each $f \in \mathcal{F}$, we know the range r_f (in km) and seat capacity s_f. Furthermore, for each flight with an aircraft of type f between nodes v and w, we are given the cost c^f_{vw} and CO_2-emissions e^f_{vw}, which are fixed based on a fully occupied plane. We model the passenger demand between each node pair (v, w) as an individual commodity, resulting in an overall multi-commodity flow formulation. To that end, we let $\mathcal{P}_{vw}$ denote the set of all feasible paths between v and w in G, for each node pair (v, w). Thus, a path indicates the selected route and also the selected aircraft type. Moreover, $\mathcal{P}$ denotes the set of all feasible paths between all node pairs. Hence, we employ variables $x_p \in [0, 1]$ that denote the percentage of demand d_{vw} being routed along a path $p \in P_{vw}$, and we let $\hat{e}_p$ and $\hat{c}_p$ denote the emissions produced and costs incurred, respectively, if the entire demand d_{vw} is transported via path p.

Finally, we have variables $z_v \in \{0, 1\}$ for all $v \in V$ to decide whether or not airport v should be enabled for electric flights, i.e., respective infrastructure investments should be made. The total investment is limited by a budget parameter B, which must not be exceeded.

Now, our overall model—also referred to as the *leader problem*—can be stated as follows:

$$
\begin{aligned}
\min \quad & \sum_{p \in P} \hat{e}_p \cdot x_p && && (1)\\
\text{s.t.} \quad & \sum_{p \in P_{vw}} x_p = 1 && \forall v, w \in V : v \neq w && (2)\\
& \sum_{\substack{p \in P: \\ E^e \cap \delta(v) \cap p \neq \emptyset}} x_p \leq M \cdot z_v && \forall v \in V && (3)\\
& \sum_{v \in V} c_v \cdot z_v \leq B && && (4)\\
& \sum_{p \in P} \hat{c}_p \cdot x_p = \mathrm{APSP}(z) && && (5)\\
& x_p \in [0,1] && \forall p \in P && (6)\\
& z_v \in \{0,1\} && \forall v \in V && (7)
\end{aligned}
$$

The objective function (1) minimizes the total emissions over all paths. Constraint (2) ensures that the total demand for each commodity is fulfilled. For sufficiently large M (cf. (13)), constraint (3) ensures that electric aircraft only operate at airports with the necessary infrastructure. Constraint (4) sets an upper bound on the investment budget for global infrastructure development.

The leader problem is a combination of two well-known optimization problems: Firstly, the model includes a facility location component that determines which airports to electrify; these decisions identify the edges on which electric aircraft can operate. Secondly, a multi-commodity flow formulation is used to determine how aircraft are routed through the network. In fact, constraint (5) ensures that only solutions in which the path variables are also optimal in terms of operating costs are allowed. We will refer to the version of the problem with continuous z-variables as the *relaxed leader problem.*

The operating costs in the lower level, which in our case correspond to an all-pairs shortest path problem, will be referred to as the *follower problem.* We use the following edge-based formulation:

$$
\begin{aligned}
\mathrm{APSP}(z) \coloneqq \min \; & \sum_{v,w \in V} d_{vw} \cdot \sum_{\{i,j\} \in E} c_{ij} \cdot f_{ij}^{vw} \\
\text{s.t.} & \sum_{j \in V} f_{ij}^{vw} - f_{ji}^{vw} = \begin{cases} 1, & i = v \\ 0, & i \notin \{v,w\} \\ -1, & i = w \end{cases} \quad \forall v, w \in V \\
& \sum_{v,w \in V} f_{ij}^{vw} \leq z_i \cdot z_j, \quad \forall \{i,j\} \in E^e \qquad (8)\\
& f_{ij}^{vw} \geq 0
\end{aligned}
$$

Here, constraint (8) ensures that electric aircraft can only be used on edges if the incident airports have been expanded with the necessary infrastructure as indicated by the given solution values of the (upper-level) z-variables. We note that since no capacity constraints are imposed on nodes or edges, the APSP formulation suffices for our purposes, as the overall cost-optimal solution can be assembled from the individual shortest paths of each commodity pair.

3.1. Solution Approach

We propose a column generation framework (cf. (14)) customized to our problem setting. Starting from a subset of all possible routes, the framework dynamically adds only the path variables x_p that are needed during the solution process, allowing efficient handling of the otherwise exponential route space. In order to address the inherent bilevel structure of our model, a set of constraints is developed that transform the problem into a single-level mixed-integer program (MIP). A central challenge in this approach is to ensure that these constraints are compatible with the column generation framework, allowing a correct integration into the overall solution method. We define the graph resulting from a given electrification selection as

$$G_z \coloneqq (V, E_z), \text{ where } E_z \coloneqq E \setminus \big\{\{v,w\} \in E^e \,:\, z_v \cdot z_w = 0\big\};$$

thus, $G_0 = (V, E \setminus E^e)$ corresponds to the graph without any edges associated with electric aircraft. The set of all v-w-paths in G_z is denoted by $P_{vw}(G_z)$. Since the solution of the leader problem has to be cost-optimal due to constraint (5) on the one hand, but has no restrictions on the capacity of the aircraft types on the other hand, there are only two relevant aircraft types for each edge. One is the cost-optimal conventional aircraft, and the other is the cost-optimal electric aircraft (if admissible). These may vary from one edge to the next. Thus, we may and do assume that the graph G_z is simplified accordingly, and that consequently, there are at most two edges between each pair of nodes.

With this in mind and given the fact that whenever an electric aircraft can fly some route, there is always at least one conventional aircraft capable of flying this route as well, we can define the following: For each pair of nodes v and w connected by both an electric e^e and conventional edge e^c, we define the cost benefit that the electric edge provides with $c^r_{vw} = \max\{c_{e^c} - c_{e^e}, 0\}$. If no electric edge exists between v and w the cost benefit is defined as zero. In addition, for every path $p \in G$, we can define a corresponding path $p' \in G_0$ that visits the same nodes but only uses conventional edges. Using these definitions, we can address the all-pairs shortest path constraint and the resulting bilevel formulation by introducing a suitable set of constraints. Since our approach relies on a column generation framework and solves the pricing problem through dynamic programming, any constraints that we introduce must be compatible with the dynamic programming procedure.

We introduce the following set of constraints that replace constraint (5) by eliminating paths whose costs exceed that of optimal paths under a given electrification scenario:

$$\sum_{p \in P_{vw}} \hat{c}_p \cdot x_p \leq \hat{c}_{p'} - d_{vw} \sum_{\{i,j\} \in p'} c^r_{ij} \cdot \omega^e_{ij} \forall v, w \in V : v \neq w, \forall\, p' \in P_{vw}(G_0), \tag{9}$$

where the auxiliary variables w are defined as

$$\omega^e_{vw} = z_v \cdot z_w \qquad \forall v, w \in V,\, v \neq w. \tag{10}$$

Using the McCormick inequalities [26], we get the exact linearization

$$\begin{aligned} \omega^e_{vw} = z_v \cdot z_w \quad \Leftrightarrow \quad & 0 \leq \omega^e_{vw} \leq z_w, \\ & z_w + z_v - 1 \leq \omega^e_{vw} \leq z_v. \end{aligned} \tag{11}$$

Note that the constraints (9) essentially correspond to an optimal-value reformulation (cf. [21]) of the bilevel follower constraint (5). Consequently, replacing (5) by (9) (and including (11)) in the original formulation yields an equivalent model. For the sake of completeness, we formalize this result and provide a short proof:

Proposition 3.1. *Let $v, w \in V, v \neq w, z \in \{0,1\}^n$, and $p \in P_{vw}(G_z)$. Then, it holds that*

$$p \in SP_{vw}(G_z) \Leftrightarrow \forall\, p' \in P_{vw}(G_0) : \hat{c}_p \leq \hat{c}_{p'} - d_{vw} \sum_{\{i,j\} \in p'} c^r_{ij} \cdot z_i \cdot z_j,$$

where $SP_{vw}(G_z)$ denotes the set of shortest paths from v to w in G_z with respect to the operating costs c.

Proof. Let $p \notin SP_{vw}(G_z)$. Then there exists a path $p' \in P_{vw}(G_z)$ with $\hat{c}_{p'} < \hat{c}_p$. Under the assumptions made, one can construct the unambiguous path $p'_s \in P_{vw}(G_0)$ from p' by replacing every edge $e = \{f, g\} \in p' \cap E^e$ with the unique $\{f, g\}$-edge $e' \in E \setminus E^e$. Thus, it follows that

$$\hat{c}_p > \hat{c}_{p'} = \hat{c}_{p'_s} - d_{vw} \sum_{\{i,j\} \in p'_s} c^r_{ij} \cdot z_i \cdot z_j.$$

Conversely, let $p \in SP_{vw}(G_z)$. Suppose there exists a path $p'_s \in P_{vw}(G_0)$ with

$$\hat{c}_p > \hat{c}_{p'_s} - d_{vw} \sum_{\{i,j\} \in p'_s} c^r_{ij} \cdot z_i \cdot z_j.$$

Then, by the same construction as above, there exists another path $p' \in (G_z)$ with $\hat{c}_p > \hat{c}_{p'_s} - d_{vw} \sum_{\{i,j\} \in p'_s} c^r_{ij} \cdot z_i \cdot z_j = \hat{c}_{p'}$. However, this contradicts the fact that p is a shortest v-w-path in G_z. $\square$

To efficiently manage the vast number of possible routes, we employ a column generation framework, dynamically generating relevant path variables x_p during the solution process. To that end, we associate the dual variables $\pi_{vw} \in \mathbb{R}$ for each node pair $v, w \in V$, $v \neq w$, with the respective constraint (2), $\varphi_v \in \mathbb{R}_{\leq 0}$ for each edge $v \in V$ with $\rho \in \mathbb{R}_{\leq 0}$ with (4), as well as $\varepsilon_p \in \mathbb{R}_{\leq 0}$ for each constraint already generated for paths $p \in P_{vw}(G_0)$.

In the pricing problem, improving paths are sought in the graph G to generate alternative route compositions. An introduction to column generation is provided in [7]. Our corresponding pricing problem is formulated as follows:

$$\max_{v,w \in V} \max_{p \in P_{vw}} \pi_{vw} + \sum_{p' \in S_{vw}} \hat{c}_p \cdot \varepsilon_{p'} + \Bigg(\sum_{\substack{v \in p: \\ \{e \in E^e : \, e \in \delta(v)\} \cap p \neq \emptyset}} \mathbb{1}_{\{e \in E^e\}}(\varphi_v) \Bigg) - \hat{e}_p$$

Thus, the resulting pricing problem is of the shortest path type, and can be solved very efficiently using Dijkstra's algorithm.

For a path p to be considered for addition, the dual variables ϕ_v must be included as cost contributions in the pricing problem for every node v with at least one incident electric edge to the path p. However, if a path p traverses a node v via electric edges, the dual variables φ_v for its associated constraint needs only be accounted for once. Therefore, it is necessary to keep track of whether a node has already been reached via an electric edge or not. This could either be addressed by duplicating the graph and distinguishing between nodes reached via an electric edge and those that are not, or by adjusting constraint (3) as follows:

$$\sum_{e \in E^e \cap \delta(v)} \sum_{\substack{p \in P: \\ e \in p}} x_p \leq M \cdot z_v \qquad \forall v \in V. \tag{12}$$

In this case, the Big-M value M can be appropriately bounded from above:

$$M \leq \max_{v \in V} \sum_{e \in E^e \cap \delta(v)} \sum_{\substack{p \in P: \\ e \in p}} x_p \leq \max_{v \in V} \sum_{\substack{p \in P: \\ p \cap \delta(v) \neq \emptyset}} 2 \cdot x_p \leq \sum_{\substack{(v,w) \in V^2 \\ v \neq w}} 2 \cdot \underbrace{\sum_{p \in P_{vw}} x_p}_{=1} \leq 2 \cdot |V| \cdot (|V| - 1). \tag{13}$$

Taking this adjustment into account, our pricing problem becomes:

$$\max_{v,w \in V} \max_{p \in P_{vw}} \pi_{vw} + \sum_{p' \in S_{vw}} \hat{c}_p \cdot \varepsilon_{p'} + \sum_{a = \{f,g\} \in p} \mathbb{1}_{\{e \in E^e\}}(\varphi_f + \varphi_g) - \hat{e}_p,$$

where the indicator function $\mathbb{1}_A : X \to \{0, 1\}$ for a set $A \subseteq X$ is defined as

$$\mathbb{1}_A(x) := \begin{cases} 1, & \text{if } x \in A, \\ 0, & \text{if } x \notin A. \end{cases}$$

This corresponds to determining the maximum of the optimal values of the independent subproblems for each node pair $v, w \in V$ with $v \neq w$:

$$\begin{aligned} &\max_{p \in P_{vw}} \; \pi_{vw} + \sum_{p' \in S_{vw}} \hat{c}_{p'} \cdot \varepsilon_{p'} + \sum_{a=\{f,g\} \in p} \mathbb{1}_{\{e \in E^e\}}(\varphi_f + \varphi_g) - d_{vw} \cdot \sum_{e \in p} e_a \\ &\quad = \pi_{vw} - \min_{p \in P_{vw}} \sum_{p' \in S_{vw}} \hat{c}_{p'} \cdot (-\varepsilon_{p'}) + \sum_{a=\{f,g\} \in p} \mathbb{1}_{\{e \in E^e\}}(-\varphi_f - \varphi_g) + d_{vw} \cdot \sum_{e \in p} e_a \\ &\quad = \pi_{vw} - \min_{p \in P_{vw}} d_{vw} \cdot \sum_{a=\{f,g\} \in p} \Big(\sum_{p' \in S_{vw}} (-\varepsilon_{p'}) \cdot c_a \Big) + \mathbb{1}_{\{e \in E^e\}}(-\varphi_f - \varphi_g) + e_a. \end{aligned} \tag{14}$$

Since this pricing problem (14) depends on the set of constraints of type (9) and these constraints are to be generated during the solving process, we proceed as follows. The leader problem is first solved while considering the constraints (9) generated so far—initially, none. The obtained solution is then assessed with respect to constraints that were not initially included in the model. Upon detecting any violations, additional constraints of type (9) are generated for all impacted paths and added to the leader problem. The pricing problem is updated accordingly and the restricted leader problem, which has been extended by new cutting plans, must be solved to optimality again. This iterative process repeats until no further violated constraints are detected.

To avoid generating a large number of paths in the pricing problem that later become infeasible, the shortest path problem can be extended to include a resource constraint. On the one hand, this will lead to a significant increase in computation time for the pricing calls due to the general NP-hardness of the shortest path problem with resource constraints (SPPRC). On the other hand, it is possible to prevent a significant number of paths from being generated that are not taken into account by the follower decision and therefore do not belong to any optimal solution.

The corresponding SPPRC reads as follows: Search for improving paths exclusively among paths that are more advantageous in terms of operating cost than the best path that uses edges in $A \setminus A^e$ only, and can therefore be selected without infrastructure expansion.

To that end, let $\hat{q}^c_{vw}$ be the cost of the cheapest $v-w$-path with respect to the operating cost c in G_0. The SPPRC is obtained by reformulating the second part of the original pricing problem. This leads to independent subproblems for each pair of nodes, which have the form

$$\begin{aligned} \min_{p \in P_{vw}} \quad & d_{vw} \sum_{a=\{f,g\} \in p} \sum_{p' \in S_{vw}} (-\varepsilon_{p'}) \cdot c_a + \mathbb{1}_{\{e \in E^e\}}(-\varphi_f - \varphi_g) + \hat{e}_a \\ \text{s.t.} \quad & \sum_{e \in p} c_a \leq \hat{q}^c_{vw}. \end{aligned}$$

4. Computational Results

To evaluate the computational performance and scalability of the proposed optimization method, we conducted a series of experiments. The algorithm was implemented in C++ using the SCIP 9.2.0 optimization [3] framework, with Gurobi 11.0.0 serving as the underlying linear program (LP) solver. All computations were performed on a MacBook Pro equipped with an Apple M2 Pro chip (10-core CPU, 16-core GPU) and 32 GB of unified memory. The source code and data can be accessed online [18].

The instance size is primarily determined by the number of candidate airports, which directly influences both the number of potential electrification decisions and the number of commodity pairs. Furthermore, the computational time is influenced by the budget level. For the computa-

Table 1: Overview of computation times

inst. no.	# airports	budget [1000×10^6 €]	# cols	# rows	# nodes	time (s)
1.	5	1	65	47	13	0.10
2.	5	1	47	47	8	0.07
3.	5	1	61	47	10	0.08
4.	5	1	67	47	12	0.08
5.	5	1	75	47	20	0.10
6.	10	2	394	192	77	1.31
7.	10	2	461	192	109	1.34
8.	10	2	467	192	109	1.39
9.	10	2	475	192	200	2.07
10.	10	2	479	192	149	1.69
11.	15	3	1492	437	2093	66.59
12.	15	3	1492	437	1466	48.57
13.	15	3	1321	437	984	35.75
14.	15	3	1490	437	1633	54.19
15.	15	3	1424	437	1350	45.43
16.	20	4	3023	782	9613	857.66
17.	20	4	3172	782	13 612	1189.82
18.	20	4	3131	782	11 001	968.11
19.	20	4	3184	782	15 672	1367.21
20.	20	4	3166	782	16 067	1387.14
21.	25	5	4788	1226	-	>7200

tional tests, uniform electrification costs were assumed and the budget was set to a level sufficient to allow approximately one third of all airports to be electrified.

Table 1 summarizes the computation times required to solve problem instances of increasing size to optimality. The results indicate that the model remains computationally tractable for instances involving up to 20 airports. However, for the 25-airport instance, the solver was unable to find an optimal solution within a two-hour time limit.

Two alternative adaptations were tested to enhance computational efficiency, but neither improved the solution time . The first adaptation involved reformulating the problem as a Shortest Path Problem with Resource Constraints (SPPRC). When applied to the same instances, this approach did not reduce computational time. Detailed runtime statistics for this formulation can be found in Table B.1 in Appendix B. The second adaptation replaced the original constraints (5) with an equivalent formulation derived from the strong duality and dual feasibility conditions of the subproblem. This duality-based formulation produced similar computational times as the initial approach and offered no computational advantage.

4.1. Dataset and Scenarios

To ensure that the model closely reflects real-world conditions, we use the operational cost and CO_2 emission estimates provided by Förster et al. [14] based on route characteristics and aircraft type. Fuel and electricity prices were obtained from [17] and [33], respectively. Since no official data on passenger demand between specific origin-destination airport pairs is freely available, we relied on the model developed by Tillmann et al. [35]. This model estimates OD-passenger demand using various socio-economic and geographic indicators associated with each airport region.

Unfortunately, nearly no reliable data appears to be published reagarding the infrastracture cost required for the deployment of electric aircraft. The only such estimate we are aware of can be found in [39], which provides a general indication of the magnitude of costs, albeit no

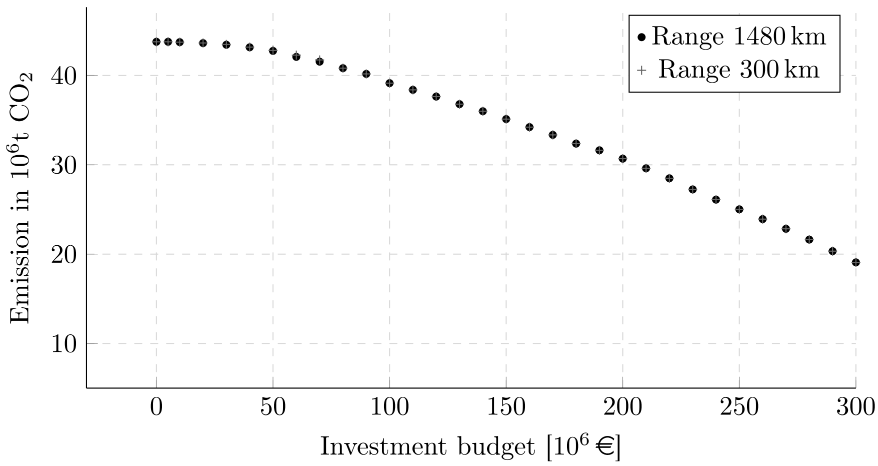


Figure 1: Scenario 1: Impact of varying investment budget on the total produced emissions [CO_2].

precise value. They suggest that the cost of infrastructure development at larger airports is disproportionately higher than at smaller facilities. As it is uncertain whether this assumption reflects reality, but it can generally be expected that costs increase with passenger volume, we consider two scenarios: Scenario 1 assumes that expansion costs rise in large discrete steps, whereas Scenario 2 assumes that infrastructure costs scale proportionally with the estimated passenger volumes reported in [35].

The application of the model is demonstrated using a case study involving 20 airports in Germany. A detailed list of the considered airports along with their relevant parameters is provided in Table 2 in appendix A. Since electric aircraft can only serve routes within a limited distance, their range imposes a significant constraint on feasible airport connections. It is therefore essential to examine how different range assumptions affect the set of airports ultimately selected for electrification. We focus on two key aspects to analyze: First, how robust the electrification decisions are with respect to the estimated operating range of an electric aircraft; second, how the importance of individual airports varies with regard to the centrality to their respective locations. To that end, we consider both scenarios, each with a pessimistic operational range of an electric aircraft of 300 km and an optimistic one of 1480 km as specified in [14].

4.2. Evaluation

Our initial investigation will focus on determining which airports are selected under different budget limits and whether identifiable patterns emerge in the selection. The optimal airport selection and the corresponding produced emissions for a range of budget limits are determined for both scenarios. A direct comparison between the budget levels of the two scenarios is not possible due to the significant differences in investment costs between them. Nevertheless, it is possible to identify both similarities and differences in the model outcomes.

4.2.1. Scenario 1

Figure 1 illustrates the emissions produced starting with Scenario 1 across varying budget levels for the defined operational ranges. Starting with a budget of approximately 10×10^6 €, emissions begin to decrease monotonically for both ranges. Notably, the difference in emission savings between the two configurations is negligible, and beyond a budget of 70×10^6 €, there is no significant difference at all. This pattern can be further examined by analyzing the marginal emission savings per additional unit of budget (see Figure 2). Overall, a positive trend emerges: increasing the budget consistently leads to improved emission reductions, suggesting that each additional Euro is generally effective. It is important to consider the discontinuous shifts in the

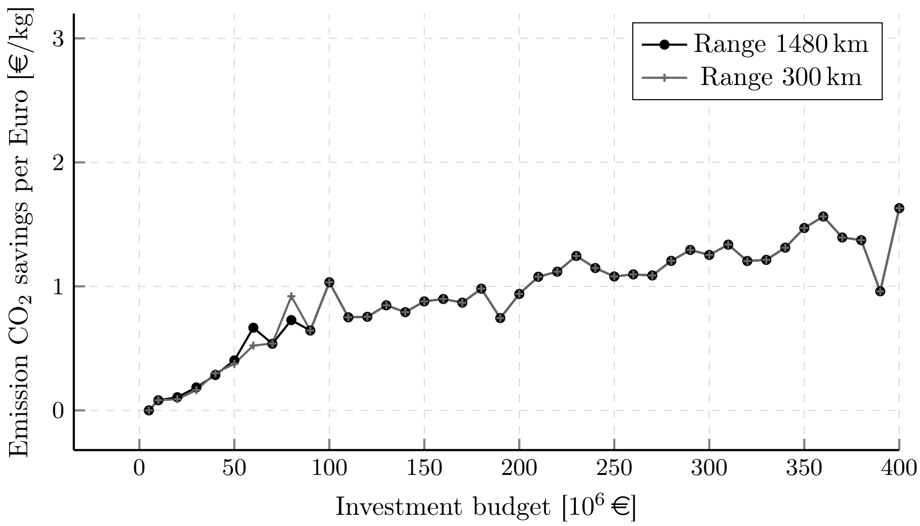


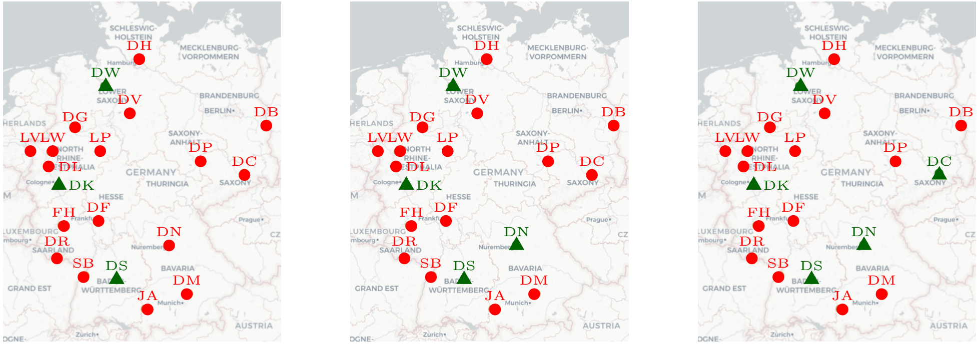
Figure 2: Scenario 1: Marginal savings of additional budget.

optimal solutions that can be observed with finer discretizations, as the solution only changes when a better alternative becomes available in the increased budget.

An analysis of the corresponding solutions reveals several key observations. While all airport pairs can be directly connected using electric aircraft with a range of 1480 km, this is not feasible with a more limited range of 300 km. A detailed examination of the solutions for budgets between 6×10^6 € and 8×10^7 € (see Figure 3) shows that, under the 300 km constraint, the airport in Nuremberg (DN) plays a critical role as an intermediate hub. It facilitates connectivity between the airport near Stuttgart (DS) in the southwest and the airport in Dresden (DC) in the east, which cannot be linked directly with electric aircraft. A similar pattern is observed for the route between Stuttgart (DS) and Bremen (DW), where the airport in Cologne (DK) is used as a stopover. However, beyond a budget of 8×10^7 €, each optimal solution in Scenario 1 for an operational range of 1480 km establishes a network of airports equipped for electric aviation that remains fully connected even with a 300 km range. As a result, the selected configurations no longer differ in terms of emissions beyond this point.

By examining incremental solutions (see Figure 4) at higher budget levels—where the outcomes no longer differ between ranges of 300 km and 1480 km—it becomes possible to identify airports that offer particularly high value for early electrification. In this scenario, medium-sized airports are among the first to be electrified and emerge as particularly valuable candidates for early infrastructure investment. Notably, the airports that served as essential bridging hubs for connecting different regions of Germany—specifically for aircraft with a limited range of 300 km—also fall into this category. As a result, once these key airports are electrified, the solutions are close together even at relatively low budget levels. In addition, there are only slight variations between the solutions regarding the corresponding airport selection: airports that are electrified early tend to remain part of the optimal configuration across different (higher) budget levels. This stability could be leveraged strategically by prioritizing a gradual expansion of electric aviation infrastructure at these consistently selected airports.

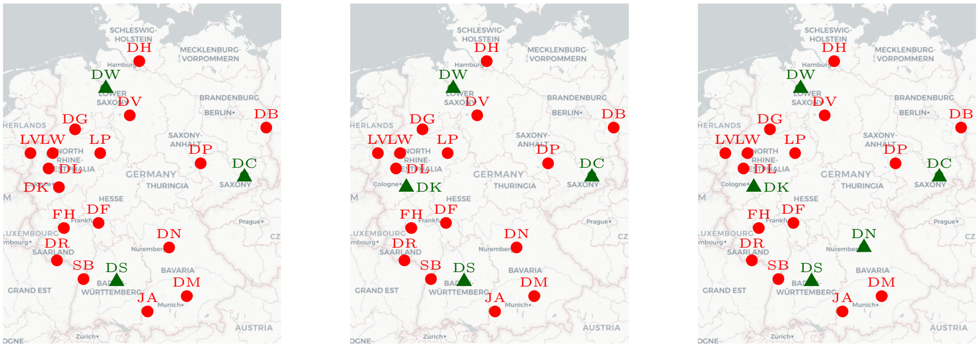
When revisiting the optimal solution for the budget level of 90×10^6 € shown in Figure 3, and examining not only the airport selection but also the resulting routing decisions, a potential limitation becomes apparent. Specifically, the connection between Bremen (DW) and Dresden (DC) requires two intermediate stops—via Cologne (DK) and Nuremberg (DN)—when operating under the constraint of an aircraft with a 300 km range. From a purely economic standpoint of the airline, such a routing remains advantageous, as electric flights offer a substantial cost benefit compared to conventional kerosene-powered operations under our assumptions. However, the



(a) Budget: 50×10^6 €, Range: 300 km

(b) Budget: 70×10^6 €, Range: 300 km

(c) Budget: 90×10^6 €, Range: 300 km

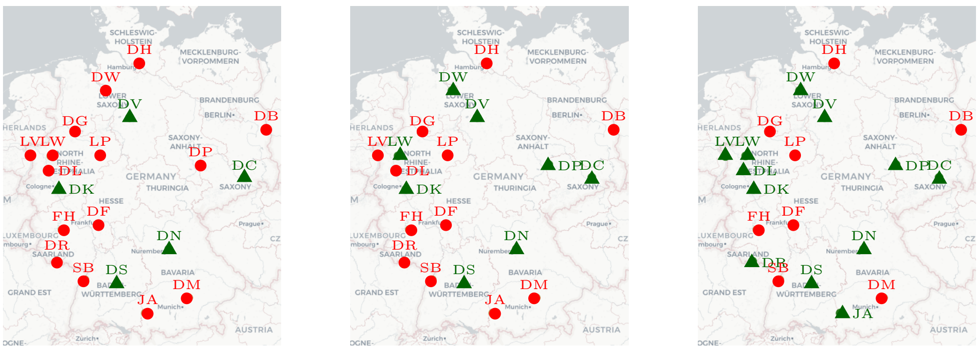


(d) Budget: 50×10^6 €, Range: 1480 km

(e) Budget: 70×10^6 €, Range: 1480 km

(f) Budget: 90×10^6 €, Range: 1480 km

Figure 3: Scenario 1: Electrification decisions for different investment budgets for the 20 largest airports in Germany; green triangles indicate airports selected for infrastructure development. Visualizations created with Plotly [29].



(a) Budget: 100×10^6 €, Range: 300 km

(b) Budget: 150×10^6 €, Range: 300 km

(c) Budget: 200×10^6 €, Range: 300 km

Figure 4: Scenario 1: Electrification decisions for different investment budgets for the 20 largest airports in Germany; green triangles indicate airports selected for infrastructure development. Visualizations created with Plotly [29].

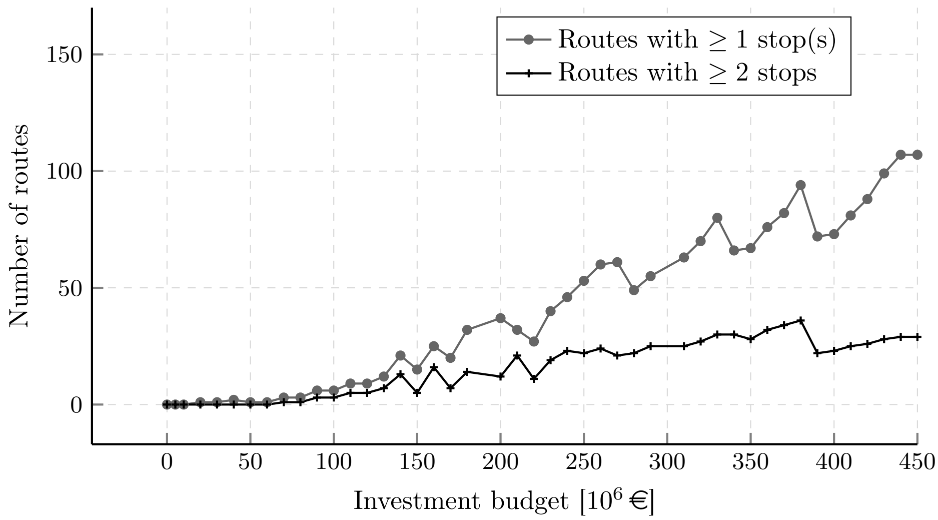


Figure 5: Scenario 1: Number of routes with transfers under different budget levels; range 300km.

number of intermediate stops raises concerns regarding passenger acceptance, particularly with respect to the willingness to make two transfers in order to avoid a five-hour car journey. The extent of this issue is further reflected in Figure 5, which indicates the number of routes that require one or more transfers. The graph shows that, under an emissions-minimizing objective, a 300 km range for electric aircraft results in itineraries with a substantial number of transfers, as even with a budget that integrates all airports into the electric network, more than a quarter of flights require at least one transfer and more than one in eight require at least two.

4.2.2. Scenario 2

In Scenario 2, differences in emission savings persist across a wider range of budget levels, although these differences are insignificant, see Figure 6. Similarly to Scenario 1, a general trend of decreasing emissions with an increasing budget can be observed. However, in contrast to Scenario 1, the rate of emission reduction becomes increasingly more pronounced for both operational ranges as the budget grows. The last observable difference in produced emissions occurs at a budget level of 450×10^6 €, at which point approximately half of the available airports are electrified and the operational range no longer influences emission outcomes.

When first considering the selection of airports across different budget levels for an operational range of 1480 km in Scenario 2 (Figure 7), a notable difference becomes apparent compared to Scenario 1: While medium-to-large airports were predominantly selected early in Scenario 1, Scenario 2 yields a prioritization of airports with the highest passenger volumes in order to get the maximal emission reductions. For example, Berlin (DB) is already equipped with the necessary infrastructure at a budget of 170×10^6 €, and by 400×10^6 €, the three largest airports in terms of passenger throughput are included in the electrified network.

At a budget of 170×10^6 €, for instance, the airports in Berlin (DB) and Nuremberg (DN) are selected under the 1480 km range, but would remain isolated in the flight network consisting exclusively of electric airplanes if it were to be operated under the limited range of 300 km. Similarly, at budget levels of 300×10^6 € and 400×10^6 €, the restricted range leads to a fragmented electric network (see Figure 7), particularly between the southeastern and northwestern regions, thereby limiting the effectiveness of electrified air transport. For that reason, for the budget of 170×10^6 €, Munich Airport (DM) is selected instead of Berlin (DB), as it can connect to the network via Karlsruhe (SB), while at other budget levels (namely 300×10^6 € and 400×10^6 €), Hannover (DV) is included in place of Dusseldorf (DL) or Dresden (DC), respectively, to ensure that no airport remains completely isolated.

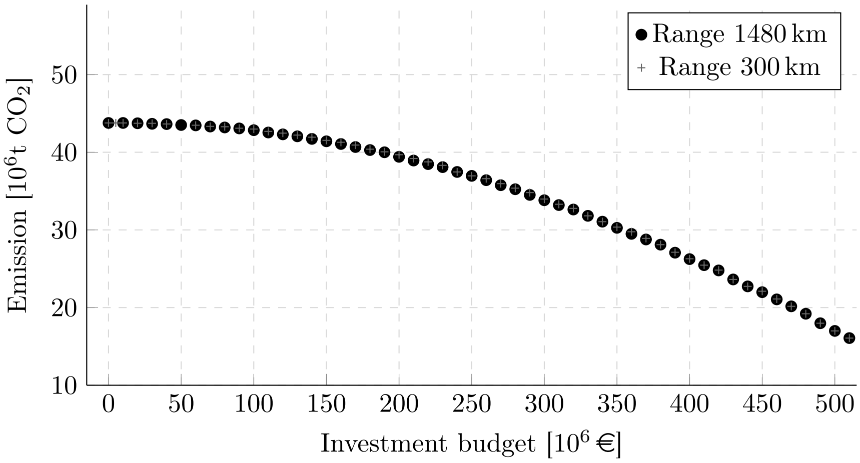
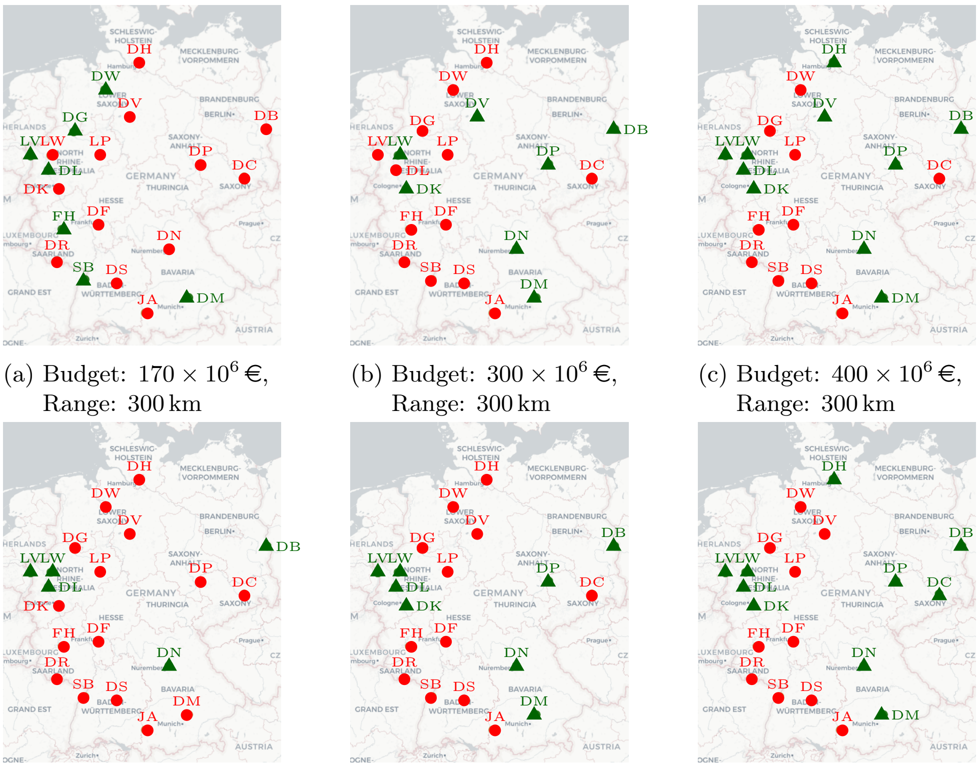


Figure 6: Scenario 2: Impact of varying investment budget on the total produced emissions (in tons of CO_2).



(a) Budget: 170×10^6 €, Range: 300 km

(b) Budget: 300×10^6 €, Range: 300 km

(c) Budget: 400×10^6 €, Range: 300 km

(d) Budget: 170×10^6 €, Range: 1480 km

(e) Budget: 300×10^6 €, Range: 1480 km

(f) Budget: 400×10^6 €, Range: 1480 km

Figure 7: Scenario 2: Electrification decisions for different investment budgets for the 20 largest airports in Germany; green triangles indicate airports selected for infrastructure development. Visualizations created with Plotly [29].

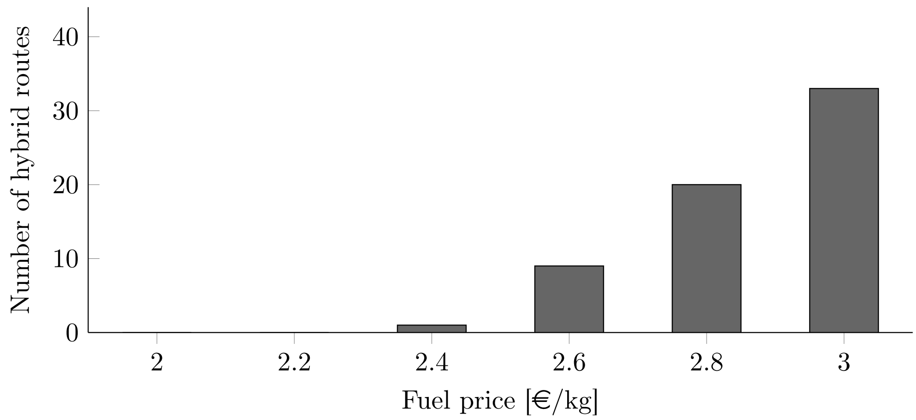


Figure 8: Impact of increasing fuel prices on the routing decisions of the model

Like in Scenario 1, an examination of the airport selection reveals that, although all routes between airport pairs within the expansion network are operated exclusively by electric aircraft, again many routes involve one or more stopovers. Notably, in both scenarios, no hybrid routing strategies—where electric and kerosene-powered aircraft are combined within a single itinerary—are used. One might intuitively expect partial electrification on longer routes, such as the connection between Munich (DM) and Saarbrucken (DR), which could theoretically be served via an intermediate stop in Karlsruhe (SB). This indicates that from the airline's perspective, any potential cost advantage of using electric aircraft on partial routes cannot be realized, as it is offset by the additional detour, the need for a subsequent or preceding kerosene-powered segment, and the associated take-off and landing fees (cf. [14]). As a result, such mixed operations do not appear to be economically viable overall.

To explore this aspect further, we systematically varied fuel and electricity prices to assess the economic threshold at which replacing only segments of a route with electric aircraft becomes favorable. This sensitivity analysis was conducted using an operational range of 1480 km, allowing for meaningful comparisons between direct and multi-leg routes.

The analysis reveals that, under the initial fuel and electricity price settings, (partial) electrification of a path does not occur. This continues to hold true even with significant reductions in electricity prices while keeping fuel prices fixed. However, the situation shifts when fuel prices rise. As shown in Figure 8, hybrid routings involving both electric and kerosene-powered segments begin to appear once the fuel price reaches 2.4 €/kg, which is roughly four times the estimate from [17] we used in the main experiments. At this point, the economic conditions become favorable enough for airlines to consider mixed operations on certain routes, making the solutions very resistant to changes in both cost parameters. When the difference in fuel prices is contextualized with forecasted fuel prices—for instance, those projected in [9], which assumes a fuel price of up to 1.05 €/kg in 2050—a hybrid transport model involving segments operated by electric and conventional aircraft does not emerge as a viable option for short-haul routes across any of the evaluated scenarios under the given assumptions and parameters.

5. Concluding Remarks

We modeled the challenging task of identifying which airports should be enabled for electric aircraft operations and equipped with the necessary infrastructure as a bilevel optimization problem. The first stage involves making strategic decisions about airport infrastructure expansion, while the second stage determines the most cost-effective aircraft routing. The objective was to minimize the total amount of emissions produced. To solve this problem, we introduced a cutting-plane procedure to reformulate the model into a single-level mixed-integer linear program that we tackled with a column generation approach.

Our computational results show that emissions differences across various aircraft configurations are generally small, suggesting a limited overall impact. However, these marginal differences result in a higher number of intermediate stops on certain routes. In contrast, no stopovers are utilized for switching between aircraft types, meaning that partial routes operated by electric aircraft are not included in the optimal solutions. The results also reveal that the optimal configurations remain largely stable across different budget levels—a property that can be leveraged strategically to support a phased implementation. Especially under the realistic assumption that the expansion of electric aviation infrastructure will occur in multiple stages, this stability allows for early investments to be directed toward airports that not only remain part of the final, fully developed network, but are also likely to offer a high-quality solution within the budget available at the time. Nevertheless, availability of more and better data would be highly beneficial, as the reliability of the derived solutions and insights is inherently tied to the quality of the underlying data.

Our current problem formulation provides opportunities for future research and development. One such extension would be to incorporate a time-based expansion model in order to develop a phased procedure rather than assuming that near-optimal static solutions at intermediate budget levels will naturally lead to a good overall outcome. This approach would explicitly determine the optimal expansion procedure over time and minimize its produced emission within this time horizon. Another important direction for future research is to complement the airport-side infrastructure planning with considerations of fleet development on the operator side. Since airlines are likely to expand their electric aircraft fleets gradually, incorporating a time-based fleet planning component would allow for a more realistic representation of deployment dynamics. In addition, integrating fleet planning with routing decisions would enable the model to account for operational constraints such as limited aircraft availability and flight hour capacity—providing a more comprehensive and practical foundation for strategic decision-making. All potential extensions of the model must be considered with careful attention to the likely resulting increase in complexity, given that our current approach reaches its computational limits on networks with more than 20 nodes.

References

[1] Nicolò Avogadro and Renato Redondi. Demystifying electric aircraft's role in aviation decarbonization: Are first-generation electric aircraft cost-effective? *Transportation Research Part D: Transport and Environment*, 130:104191, 2024.

[2] Ashkan Barzkar and Mona Ghassemi. Electric power systems in more and all electric aircraft: A review. *Ieee Access*, 8:169314–169332, 2020.

[3] Suresh Bolusani, Mathieu Besançon, Ksenia Bestuzheva, Antonia Chmiela, João Dionísio, Tim Donkiewicz, Jasper van Doornmalen, Leon Eifler, Mohammed Ghannam, Ambros Gleixner, et al. The SCIP optimization suite 9.0. *arXiv preprint*, 2024.

[4] European Comission. Reducing Emissions from Aviation. https://climate.ec.europa.eu/eu-action/transport/reducing-emissions-aviation_en, 2025.

[5] Jordan Cox, Tom Harris, Kathleen Krah, James Morris, Xiangkun Li, and Scott Cary. Impacts of Regional Air Mobility and Electrified Aircraft on Local Grid Infrastructure and Airport Electricity Demand. Technical report, National Renewable Energy Laboratory (NREL), Golden, CO (United States), 2023.

[6] Jacques Desrosiers and Marco E Lübbecke. A primer in column generation. In Guy Desaulniers, Jacques Desrosiers, and Marius M. Solomon, editors, *Column generation*, pages 1–32. Springer, 2005.

[7] Jacques Desrosiers, Marco Lübbecke, Guy Desaulniers, and Jean Bertrand Gauthier. *Branch-and-price*. GERAD, HÉC Montréal, 2024.

[8] Marcus Efler. Pioneers in Green Aviation: Could Norwegian Electric Planes Be a Model for the Rest of the World? https://www.spiegel.de/international/business/pioneers-in-green-aviation-could-norwegian-electric-planes-be-a-model-for-the-rest-of-the-world-a-b3aef6b5-1078-4d1a-8699-ed37926797f9, July 2023.

[9] Eurocontrol. EUROCONTROL Aviation Outlook 2050. https://www.eurocontrol.int/publication/eurocontrol-aviation-outlook-2050, April 2022.

[10] European Commission and Directorate-General for Research and Innovation and Directorate-General for Mobility and Transport. *Flightpath 2050 – Europe's vision for aviation – Maintaining global leadership and serving society's needs*. Publications Office, 2011.

[11] European Union Aviation Safety Agency. European Aviation Environmental Report 2025, 2025. URL https://www.easa.europa.eu/sites/default/files/eaer-downloads/EASA_EAER_2025_BROCHURE_WEB_de_v2.pdf.

[12] Eviation.com. Alice - The All-Electric Game Changer. https://www.eviation.com/aircraft/, 2025. Accessed May 26, 2025.

[13] Reza Zanjirani Farahani, Elnaz Miandoabchi, W.Y. Szeto, and Hannaneh Rashidi. A review of urban transportation network design problems. *European Journal of Operational Research*, 229:281–302, 2013.

[14] Peter Förster, Bekir Yildiz, Thomas Feuerle, and Peter Hecker. Approach for Cost Functions for the Use in Trade-Off Investigations Assessing the Environmental Impact of a Future Energy Efficient European Aviation. *Aerospace*, 9, 2022.

[15] Albert R. Gnadt, Raymond L. Speth, Jayant S. Sabnis, and Steven R.H. Barrett. Technical and environmental assessment of all-electric 180-passenger commercial aircraft. *Progress in Aerospace Sciences*, 105:1–30, 2019.

[16] Heart Aerospace. ES-30, 2025. URL https://heartaerospace.com/es-30/. Accessed: 2025-08-15.

[17] IATA. Jet Fuel Price Monitor. https://www.iata.org/en/publications/economics/fuel-monitor/, 2025.

[18] Imke Joormann, Frederic Kroner, and Andreas M. Tillmann. Selecting_Electric_Flight_Airports, 2025. URL https://github.com/frekro/Selecting_Electric_Flight_Airports.

[19] Cedric Y. Justin, Alexia P. Payan, Simon I. Briceno, Brian J. German, and Dimitri N. Mavris. Power optimized battery swap and recharge strategies for electric aircraft operations. *Transportation Research Part C: Emerging Technologies*, 115:102605, 2020.

[20] Alan Kinene, Sebastian Birolini, Mattia Cattaneo, and Tobias Andersson Granberg. Electric aircraft charging network design for regional routes: A novel mathematical formulation and kernel search heuristic. *European Journal of Operational Research*, 309:1300–1315, 2023.

[21] Thomas Kleinert, Martine Labbé, Ivana Ljubić, and Martin Schmidt. A Survey on Mixed-Integer Programming Techniques in Bilevel Optimization. *EURO Journal on Computational Optimization*, 9, 2021.

[22] D.S. Lee, D.W. Fahey, A. Skowron, M.R. Allen, U. Burkhardt, Q. Chen, S.J. Doherty, S. Freeman, P.M. Forster, J. Fuglestvedt, A. Gettelman, R.R. De León, L.L. Lim, M.T. Lund, R.J. Millar, B. Owen, J.E. Penner, G. Pitari, M.J. Prather, R. Sausen, and L.J. Wilcox. The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018. *Atmospheric Environment*, 244:117834, 2021.

[23] Xinyu Liu and Qun Chen. An algorithm for the mixed transportation network design problem. *PlOS one*, 11:1–18, 2016.

[24] Vincenzo Madonna, Paolo Giangrande, and Michael Galea. Electrical Power Generation in Aircraft: Review, Challenges, and Opportunities. *IEEE Transactions on Transportation Electrification*, 4:646–659, 2018.

[25] Thomas L Magnanti and Richard T Wong. Network design and transportation planning: Models and algorithms. *Transportation science*, 18:1–55, 1984.

[26] Garth P. McCormick. Computability of global solutions to factorable nonconvex programs: Part I — Convex underestimating problems. *Mathematical Programming*, 10:147–175, 1976.

[27] Susan Hesse Owen and Mark S. Daskin. Strategic facility location: A review. *European Journal of Operational Research*, 111:423–447, 1998.

[28] Luke Peters. UrbanLink orders up to 20 Eviation Alice aircraft for US regional flights. https://www.aerotime.aero/articles/urbanlink-orders-eviation-alice, 2024.

[29] Plotly Technologies Inc. Collaborative Data Science. https://plot.ly, 2015.

[30] Khodakaram Salimifard and Sara Bigharaz. The multicommodity network flow problem: state of the art classification, applications, and solution methods. *Operational Research*, 22: 1–47, 2022.

[31] Andreas W Schäfer, Steven RH Barrett, Khan Doyme, Lynnette M Dray, Albert R Gnadt, Rod Self, Aidan O'Sullivan, Athanasios P Synodinos, and Antonio J Torija. Technological, economic and environmental prospects of all-electric aircraft. *Nature Energy*, 4(2):160–166, 2019.

[32] Dieter Schmitt and Volker Gollnick. *The air transport system*. Springer, 2015.

[33] Amy Schwab, Anna Thomas, Jesse Bennett, Emma Robertson, and Scott Cary. Electrification of Aircraft: Challenges, Barriers, and Potential Impacts. Technical report, National Renewable Energy Laboratory (NREL), Golden, CO (United States), 10 2021. URL https://www.osti.gov/biblio/1827628.

[34] Sahar Tahernejad, Ted K Ralphs, and Scott T DeNegre. A branch-and-cut algorithm for mixed integer bilevel linear optimization problems and its implementation. *Mathematical Programming Computation*, 12:529–568, 2020.

[35] Andreas M Tillmann, Imke Joormann, and Sabrina CL Ammann. Reproducible air passenger demand estimation. *Journal of Air Transport Management*, 112:102462, 2023.

[36] Lorenzo Trainelli, Francesco Salucci, Carlo E. D. Riboldi, Alberto Rolando, and Federico Bigoni. Optimal Sizing and Operation of Airport Infrastructures in Support of Electric-Powered Aviation. *Aerospace*, 8, 2021.

[37] Simon van Oosterom and Mihaela Mitici. Optimizing the battery charging and swapping infrastructure for electric short-haul aircraft—the case of electric flight in Norway. *Transportation Research Part C: Emerging Technologies*, 155:104313, 2023.

[38] United Airlines Ventures. Electric Aircraft Set to Take Flight by 2026 Under New Agreements with United Airlines Ventures, Breakthrough Energy Ventures, Mesa Airlines, Heart Aerospace. https://www.prnewswire.com/news-releases/electric-aircraft-set-to-take-flight-by-2026-under-new-agreements-with-united-airlines-ventures-breakthrough-energy-ventures-mesa-airlines-heart-aerospace-301331995.html, 2021.

[39] World Economic Forum. Target True Zero: Delivering the Infrastructure for Battery and Hydrogen-Powered Flight. https://www3.weforum.org/docs/WEF_Target_True_Zero_2023.pdf, 2023. Accessed: 2025-05-26.

[40] David W Wragg. *A dictionary of aviation*. Osprey Publishing, 1973.

[41] Bo Zeng and Yu An. Solving bilevel mixed integer program by reformulations and decomposition. *Optimization online*, pages 1–34, 2014.

[42] J. Zhang. Sustainable Aviation Electrification: A Comprehensive Review. *Sustainability*, 14:5880, 2022.

Appendix

A. Considered Airports in Germany

Table 2: Overview for the dataset comprising the 20 largest airports in Germany based on passenger demand estimation from [35], together with the corresponding infrastructure cost assumptions under Scenario S1 and S2

city	ICAO code	passenger demand	S1 EC [10^6 €]	S2 EC [10^6 €]
Munic	EDDM	$2.7 \cdot 10^7$	50	60
Hamburg	EDDH	$2.5 \cdot 10^7$	50	60
Berlin Brandenburg	EDDB	$2.4 \cdot 10^7$	50	50
Frankfurt	EDDF	$2.4 \cdot 10^7$	50	50
Stuttgart	EDDS	$2.0 \cdot 10^7$	20	50
Cologne/Bonn	EDDK	$1.9 \cdot 10^7$	20	40
Nuremberg	EDDN	$1.8 \cdot 10^7$	20	40
Dresden	EDDC	$1.7 \cdot 10^7$	20	40
Hanover	EDDV	$1.6 \cdot 10^7$	20	40
Dusseldorf	EDDL	$1.4 \cdot 10^7$	20	30
Leibzig/Halle	EDDP	$1.3 \cdot 10^7$	20	30
Dortmund	EDLW	$1.3 \cdot 10^7$	20	30
Saarbrucken	EDDR	$1.1 \cdot 10^7$	10	20
Bremen	EDDW	$8.7 \cdot 10^6$	10	20
Muenster/Osnabruck	EDDG	$6.1 \cdot 10^6$	10	20
Paderborn/Lippstadt	EDLP	$5.3 \cdot 10^6$	10	20
Karlsruhe/Baden-Baden	EDSB	$5.1 \cdot 10^6$	10	20
Weeze	EDLV	$4.3 \cdot 10^6$	4	10
Memmingen	EDJA	$2.5 \cdot 10^6$	4	10
Frankfurt-Hahn	EDFH	$2.2 \cdot 10^6$	4	10

B. Additional Computational Results

Table 3: Overview of computational times for the overall algorithm, comparing the solution times when the pricing problem is solved using SP and SPPRC, respectively.

inst. no.	$\|V\|$	budget [10^6 €]	fuel cost [€/kg]	electricity cost [€/kWh]	SPPRC [s]	SP [s]
1.	20	2	0.8	0.13	1839.32	521.20
2.	20	2	1.2	0.13	1852.30	545.92
3.	20	2	1.6	0.13	1870.83	559.78
4.	20	3	0.8	0.13	2895.75	2162.60
5.	20	3	1.2	0.13	2926.88	2009.33
6.	20	3	1.6	0.13	2970.52	1626.58
7.	20	4	0.8	0.13	2679.14	1453.86
8.	20	4	1.2	0.13	2733.11	1607.14
9.	20	4	1.6	0.13	2794.82	1877.23