Optimizing Electrified Aviation Networks

MSc Thesis

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TUDelft

Optimizing Electrified Aviation Networks: Strategic Planning Under Spatiotemporal Electricity Price Dynamics

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Nomenclature

Abbreviations

Abbreviation	Definition
ASK	Available Seat-Kilometer
BSS	Battery Swaps System
CAL	Capital Allocation Line
CASK	Cost per Available Seat Kilometer
CPI	Consumer Price Index
CV	Coefficient of Variation
E9X	Elysian E9X concept aircraft
EA	Electric Aircraft
EHAM	Amsterdam Airport Schiphol (ICAO code)
EIA	Energy Information Administration (U.S.)
ERJ	Embraer Regional Jet
ETS	EU Emissions Trading System
EU	European Union
FAP	Fleet Assignment Problem
HCIP	Harmonized Index of Consumer Prices
IATA	International Air Transport Association
LCC	Low-Cost Carrier
MFAP	Mixed-Fleet Assignment Problem
MILP	Mixed Integer Linear Programming
O-D	Origin-Destination
P2P	Point-to-Point
PICS	Plug-in Charging System
PSO	Public Service Obligation
RASK	Revenue per Available Seat-Kilometer
RPK	Revenue Passenger-Kilometer
SAF	Sustainable Aviation Fuel
SD	Standard Deviation
SoC	State of Charge
SSTEAP	Strategic Spatiotemporal Electricity-Aware Planning
TaT	Turnaround Time
VoK	Value of Knowledge

Symbols

Symbol	Definition	Unit
Sets and Indices		
$\mathcal{A}$	Set of airports, indexed by i, j	-
$\mathcal{T}$	Set of available aircraft types, indexed by a	-
$\mathcal{T}_e$	Subset of electric aircraft types, $\mathcal{T}_e \subseteq \mathcal{T}$	-
$\mathcal{T}_k$	Subset of kerosene aircraft types, $\mathcal{T}_k \subseteq \mathcal{T}$	-
$\mathcal{R}$	Set of feasible pre-generated round-trip routes, indexed by r	-
$\mathcal{K}_r$	Ordered set of stops (positions) along a given route r, indexed by k	-
$\mathcal{L}$	Set of all unique legs (i, j) across all routes	-
$\mathcal{L}_r$	The ordered sequence of legs constituting route r	-
$\mathcal{R}_{ij}$	Subset of routes r containing the leg (i, j)	-
Parameters - Model Structure and Economic		
$A(r, k)$	Airport corresponding to stop k on route r	-
N_r	Index of the final stop on route r (number of stops including the hub)	-
L_{ij}	Distance of leg (i, j)	[km]
D_{ij}	Monthly passenger demand on leg (i, j)	[pax]
Y_{ij}	Passenger yield on leg (i, j)	[€/pax-km]
P_i^{elec}	Electricity price at airport i	[€/kWh]
P_i^{kero}	Kerosene price at airport i	[€/liter]
$C_a^{\text{op,ask}}$	Variable operating cost per available seat-kilometer for aircraft a	[€/seat-km]
C_a^{fix}	Fixed monthly cost for one aircraft of type a	[€/month]
m	Minimum profit margin per route	[-]
LF^{max}	Maximum permissible load factor	[-]
W^{max}	Maximum total fleet size	[aircraft]
W_a^{max}	Maximum number of aircraft of type a	[aircraft]
Parameters - Flight Planning and Geometry		
f_{range}	Route lengthening factor to account for imperfect flight paths	[-]
g_{climb}	Climb gradient for flight time calculation	[rad]
$h_{\text{cruise km}}$	Cruise altitude for flight time calculation	[km]
ℓ^{min}	Minimum leg distance allowed	[km]
Parameters - Aircraft Performance and Time		
S_a	Number of seats on aircraft type a	[seats]
R_a	Range of aircraft type a	[km]
V_a	Cruise speed of aircraft type a	[km/h]
H	Available block hours per aircraft per month	[hr]
F_{ij}^a	Kerosene consumed by aircraft a on leg (i, j)	[liters]
E_{ij}^a	Electricity consumed by aircraft a on leg (i, j)	[kWh]

Symbol	Definition	Unit
$B_a^{\min/\max}$	Minimum/Maximum battery state-of-charge (SoC) limits	[kWh]
P_a^{charge}	Charging power (rate) of aircraft a	[kW]
T_{ra}^{FLIGHT}	Total flight time of aircraft a on route r	[hr]
B_r^{kero}	Pre-calculated block time for a conventional aircraft on route r	[hr]
$T^{\text{MIN,TURN}}$	Minimum turnaround time for electric aircraft	[hr]
$T^{\text{kero,turn}}$	Fixed turnaround time for a conventional aircraft	[hr]
T^{SETUP}	Time required for charging setup/teardown	[hr]

Decision Variables

Symbol	Definition	Unit
$w_a \in \mathbb{Z}_{\geq 0}$	Number of aircraft of type a acquired	[aircraft]
$z_{ra} \in \mathbb{Z}_{\geq 0}$	Monthly frequency of aircraft a on route r	[routes/month]
$p_{ij} \in \mathbb{Z}_{\geq 0}$	Passengers transported on leg (i, j)	[pax]
$c_{ra,k} \in \mathbb{R}_{\geq 0}$	Electricity charged into aircraft a at stop k	[kWh]
$b_{ra,k} \in \mathbb{R}_{\geq 0}$	Battery level on arrival at stop k for aircraft a on route r	[kWh]
$t_{ra,k} \in \mathbb{R}_{\geq 0}$	Turnaround time for aircraft a at stop k (Electric only)	[hr]
$y_{ra,k}^{\text{charge}} \in \{0, 1\}$	Binary decision to charge aircraft a at stop k	[-]

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Optimizing Electrified Aviation Networks: Strategic Planning Under Spatiotemporal Price Dynamics

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Electric aircraft (EA) reliance on volatile electricity prices introduces significant financial risk, a challenge often overlooked in strategic planning. We develop a profit-maximizing Mixed Integer Linear Program (MILP) with a novel circular-route design to optimize strategic electric airline planning problems, including charge decisions and mixed fleet composition. Our results show that ignoring electricity prices can lead to >35% profit losses during volatile periods. While average prices mitigate this, accurate prices perform best, enabling charging arbitrage such as ferrying and skipping that boosts profits by 1.1% over simple heuristics. A mixed fleet of both electric and kerosene aircraft offers additional benefits, unlocking synergistic profit gains of up to 1.5% while maintaining the financial stability of a pure kerosene fleet. In such a fleet, kerosene aircraft form a network backbone, seen by a 10% kerosene fleet share covering almost 80% of routes. The path to sustainable aviation must therefore anticipate monthly network changes to remain optimal, incorporate accurate electricity prices for strategic charging optimization, and leverage mixed fleets to ease the transition to a more electrified future.

THE aviation sector faces mounting pressure to achieve environmental sustainability. The sector accounts for approximately 2.5–3% of global CO_2 emissions [3]. Although fuel efficiency has improved by 1.9% annually from 2009 to 2019 [4], the annual growth of passenger demand of at least 2.9% has outpaced these gains [5]. With projected demand growth of 3–5% [6, 7], innovative solutions are critical to reducing aviation's climate impact.

Electric aircraft (EA) have emerged as a promising solution, projected to account for 13% of emissions abatement by 2050 while reducing noise by 36–65%, maintenance costs by 20–50% [8–12], and reducing fuel costs. In recognition of this, over 300 EA projects were initiated globally since 2016 [13].

However, EAs are currently restricted by battery density to shorter ranges and passenger capacities [14]. Crucially, the transition to EA connects airline operations to the electricity grid, exposing carriers to a market characterized by high temporal and spatial price volatility, representing a fundamental shift from the historically stable jet fuel market.

Since jet fuel historically represents 26–50% of airline operating costs [15, 16], its replacement with electricity alters airline economics. Consequently, optimizing flight planning to align with favorable electricity prices is essential to ensure the financial viability of EA. This volatility creates financial risk but also opportunities for arbitrage through 'strategic charge decisions', optimizing how much to charge at each airport. This potential is enhanced by 'charge ferrying', where aircraft charge beyond the needs of the next flight to capitalize on low electricity prices. Charge ferrying incurs no environmental penalties compared to fuel tankering, which hurts performance due to the additional weight and is further discouraged by EU regulations [17, 18].

Beyond charge optimization, the introduction of EAs allows for expanding the traditional Fleet Assignment Problem (FAP) into the Mixed-Fleet Assignment Problem (MFAP), which involves both kerosene- and electric-powered aircraft. MFAP is a different planning problem due to the differing operational and energy characteristics of each aircraft type. Furthermore, dynamic MFAP could act as an inherent hedge against high energy prices through arbitrage between the decoupled electricity and kerosene markets.

The paper proceeds as follows. Section I reviews the literature, followed by the methods and data in

section II and III. The results are presented in three parts: section IV examines an electric fleet performance under dynamic pricing, section V quantifies the strategic value of price information, and section VI evaluates mixed fleets. Finally, section VII assesses model robustness, section VIII discusses implications, and section IX concludes the study.

I. Literature Study

The transition to electric aircraft replaces jet fuel prices with spatiotemporally volatile electricity prices, requiring novel airline planning strategies. Spatiotemporal refers to prices that change by location and over time. This section first analyzes the characteristics of the electricity market to explain why they warrant a new planning approach. It then evaluates existing research on electrified airline planning. Finally, it identifies a research gap and describes the contributions of this study to the field.
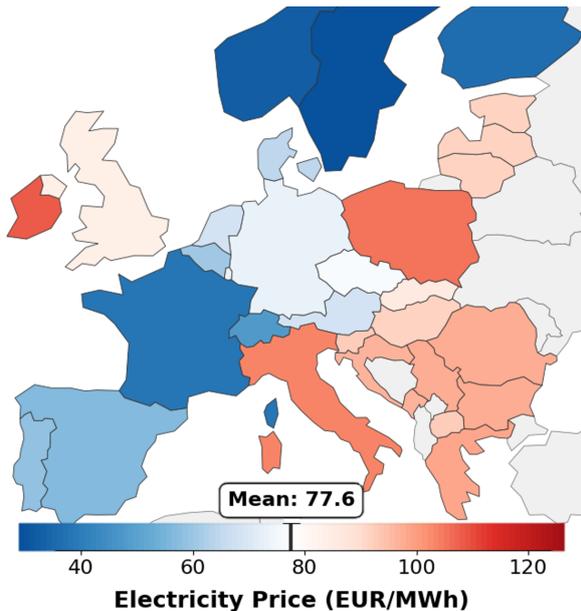
Figure 1. June 2024 Electricity Spot Prices in Europe (Large Industry Band). Grey countries are not included in the model.

A. Energy Pricing: Jet Fuel vs. Electricity

Jet fuel prices are primarily driven by crude oil prices (via the "crack spread," which is typically stable but sensitive to global events [19–21]) and, as a globally traded commodity, exhibit low spatial variation (the European Union (EU) imports 91% of its jet fuel [22]). For example, the maximum

difference between mean continental spot prices in May 2025 was only 4.14% [23].

Electricity prices are fundamentally different. As shown in Figure 1, electricity prices are highly localized. This is due to factors like national energy mixes (e.g., reliance on renewables vs. fossil fuels) [24, 25], weather-dependent generation [26, 27], limited energy storage, transmission losses (0.5–14% depending on grid type and distance) [28–30], and differing tax regimes (unlike jet fuel which is untaxed for intra-EU flights [31–36]). The consequence is significant price divergence. For example, between 2015 and 2025, the average wholesale electricity price in the most expensive European country was 3.8 times that of the cheapest, with this multiplier ranging from 0.57x to a remarkable 56.5x. Furthermore, electricity prices exhibit significant temporal volatility on all time scales (hourly, daily, seasonal) [37]. Lastly, while large consumers like airports may receive volume discounts, they also face high surcharges for unpredictable or peak power draws, necessitating careful planning of electric aircraft arrivals and charging schedules [38, 39].

These characteristics mean that electricity prices for electric aircraft vary dramatically by location and time, unlike the more stable jet fuel prices, necessitating a different planning approach.

B. Electrified Airline Planning

Traditional airline planning involves several strategic and tactical planning problems, including: fleet planning, route selection, schedule development (frequency planning, fleet assignment, timetable development), and aircraft routing [40–43]. The introduction of EA and variable electricity prices requires a review of these steps and the addition of new ones. Airline planning for EA can be divided into land- and airside planning problems.

Landside planning tackles charging constraints: siting (placement) [44], sizing (capacity and type, e.g., Plug In Charging Systems (PICS), Battery Swap Systems (BSS), Mobile Charging Stations) [45–47], and scheduling (optimizing charging times against electricity costs and operational needs)[37, 48].

Airside planning adapts traditional methods for EA-specific constraints. This includes examining how EA can better use underutilized regional airports made accessible by their short take-off distance [49, 50], the exploration of short-haul demand suitable

for electric aircraft [1, 51], and the underexplored problem of strategic charge decisions: deciding how much to charge at each airport.

Several studies have begun to integrate these aspects. Pereira [52] optimized fleet and infrastructure decisions, including trade-offs between battery charging and swapping. Others, like Van Amstel [53] and Hou et al. [54], confirmed that modest schedule flexibility reduces infrastructure costs and peak power demand. Extending this scope, Westin et al. [55] optimized network design and fleet assignment for public service obligation (PSO) routes. Uniquely, Vehlhaber and Salazar [56–58] investigated aligning EA operations with renewable energy availability, thereby indirectly addressing price variations.

The most comprehensive research pushes the boundaries of integrated strategic planning for EA. Kinene and Birolini [14, 49] developed two papers that simultaneously optimize network design, route selection, fleet assignment, scheduling, and charging infrastructure siting and sizing for a mixed fleet. Justin et al. [1] integrated nearly all airline planning problems within a sophisticated multi-objective framework that balances profit against emissions, showing the impact of battery density, network type, and fleet composition on network performance. However, despite their remarkable scope, all of these studies utilized fixed or averaged electricity prices, thereby failing to account for the strategic implications of dynamic, location-specific electricity prices [59, 60]. This shared oversight reveals a critical research gap at the intersection of strategic planning and energy-cost optimization for EA.

C. Research Gap and Contribution

Existing literature reveals a gap: the lack of airline planning models that integrate accurate electricity prices at the strategic level. While prior studies optimize infrastructure or operations using fixed prices [1, 52, 53], or infer price effects through energy generation [57, 58], none explicitly model how geographically and temporally diverse (spatiotemporal) prices influence strategic network design. The exclusion is often justified by its secondary impact relative to other major costs [59, 60], however, in aviation, even marginal gains can be key.

Consequently, the unique operational characteristics of EA warrant a fundamental expansion of the traditional strategic planning suite that remains largely unexplored in current literature. Specifically, existing models fail to integrate strategic charge decisions and dynamic mixed-fleet assignment into the high-level strategic planning process. Incorporating strategic charge decisions at this level enables arbitrage opportunities that are lost when relegated to operational windows. Furthermore, the potential of dynamic mixed-fleet reassignment to serve as a fleet-inherent hedge against energy price volatility by switching routes between kerosene and electric aircraft remains largely unexplored

This study bridges this gap by developing a comprehensive strategic planning framework that accounts for electricity market dynamics. It advances the field in three ways: first, by incorporating strategic charge decisions at the strategic planning level rather than solely in operational windows; second, by testing the impact of the fixed-price assumptions in previous literature; and third, by exploring dynamic Mixed-Fleet Assignment as a strategic hedging mechanism against energy price uncertainty.

We pose the following research questions:

1) **Strategies under spatiotemporal pricing:** What optimal planning strategies and structural decisions are revealed by an expanded electrified aviation network model that incorporates spatiotemporal electricity prices?
2) **Planning value:** What is the financial value of incorporating different granularities of electricity price information into strategic airline planning models for electrified aviation?
3) **Mixed fleet strategies:** How does the strategic composition and dynamic reassignment potential of a mixed fleet (electric and kerosene aircraft) influence overall network profitability, financial stability, and operational specialization in response to fluctuating energy prices?

II. Methodology

This section details the methodology, covering the model's design and technical formulation.

A. Modeling Scope and Design Choices

We introduce the Strategic Spatio-Temporal Electricity-Aware Planning (SSTEAP) model, formulated as a profit-maximizing Mixed-Integer Linear Programming (MILP) problem. The model simultaneously optimizes fleet size, composition,

route selection, frequency, and charging decisions for mixed fleets. It is based on common strategic airline planning MILP formulations but distinguishes itself through its unique circular route formulation, integration of electric charging decisions, mixed-type (electric/kerosene) planning capability, and incorporation of spatiotemporal electricity prices.

1. Analytical Framework

The model is designed for high-level strategic planning. It optimizes the network for each month independently, rather than producing a continuous operational schedule, allowing us to observe how the optimal strategic network responds to a changing environment. This analytical perspective justifies the use of a computationally intensive MILP formulation over faster heuristics. Aligned with this strategic focus, the model uses historical monthly data. This approach avoids the uncertainties of long-term forecasting, particularly in volatile energy markets. The study evaluates the conceptual Elysian E9X-440 electric aircraft, planned for 2033 [61]. In effect, the method moves the aircraft back in time rather than extrapolating the entire market environment into the future.

The model follows a profit-maximizing objective, a standard in airline planning that gives a clear reason for model decisions and aligns with industry profitability targets. Although the objective is financial, the structural decisions are examined in detail.

2. Circular Route Formulation

The model's network is hub-centric, aligning with early adoption strategies for EA that centralize maintenance and charging. This is implemented via a circular route architecture. While conventional models often use disjoint legs connected by node flow continuity constraints, this approach is problematic when incorporating strategic charging decisions. Ensuring battery state continuity with a leg-based model either requires solving a computationally expensive aircraft routing problem, which is beyond a strategic scope, or imposing overly restrictive, uniform assumptions about battery levels at connecting airports that would prevent intelligent energy management.

Our formulation bypasses this dilemma by optimizing over operationally complete sequences. It uses a pre-generated candidate set of all possible round-trip flights of up to three legs departing and returning to the central hub. This structure inherently guarantees aircraft location and battery-state continuity, as each route is a complete cycle that begins and ends at the hub, where aircraft must recharge fully. Crucially, this leaves the battery state at intermediate stops unconstrained, allowing the model to make sophisticated decisions such as charge ferrying. This approach remains computationally tractable within the scope of this study's large airports (<800 routes for the E9X), however, the number of potential routes grows combinatorially with more airports included. Extending the model to four-leg routes (20k+ possible routes) renders this pre-generation approach intractable; however, the three-leg scope is sufficient for the study's objectives and remains computationally tractable.

B. Model Formulation

This section presents the mathematical formulation of the SSTEAP model.

1. Sets

The formulation distinguishes between airports ($i, j \in \mathcal{A}$), which are fixed spatial locations, and stops ($k \in \mathcal{K}_r$), which represent sequential points in an aircraft's journey on a given route. The function $A(r, k)$ maps a specific stop in a route to a physical airport.

- $\mathcal{A}$: Set of airports, indexed by i or j.
- $\mathcal{T}$: Set of aircraft types, indexed by a.
- $\mathcal{T}_e \subseteq \mathcal{T}$: Subset of electric aircraft types.
- $\mathcal{T}_k \subseteq \mathcal{T}$: Subset of kerosene aircraft types.
- $\mathcal{R}$: Set of feasible round-trip routes, indexed by r.
- $\mathcal{K}_r$: Ordered set of stop indices in route r, $k \in \{0, 1, \ldots, N_r\}$. Stops $k = 0$ and $k = N_r$ correspond to the hub airport.
- $\mathcal{L}$: Set of all unique legs (i, j) across all routes.
- $\mathcal{L}_r \subseteq \mathcal{L}$: The ordered sequence of legs constituting route r.
- $\mathcal{R}_{ij} \subseteq \mathcal{R}$: Subset of routes r containing the leg (i, j).

2. Parameters

- $A(r, k) \in \mathcal{A}$: Airport corresponding to stop k on route r.
- N_r: Index of the final stop on route r.
- L_{ij}: Distance of leg (i, j) (km).
- F_{ij}^a: Kerosene consumed by aircraft a on leg (i, j) (L).
- E_{ij}^a: Electricity consumed by aircraft a on leg (i, j) (kWh).
- D_{ij}: Monthly passenger demand on leg (i, j).
- Y_{ij}: Passenger yield on leg (i, j) (€/pax-km).
- $P_i^{\text{kero}}, P_i^{\text{elec}}$: Kerosene and electricity prices at airport i.
- S_a: Seat capacity of aircraft type a.
- $C_a^{\text{op,ask}}$: Operating cost for aircraft a (€/ASK).
- C_a^{fix}: Fixed monthly cost of aircraft type a (€).
- H: Maximum monthly block hours per aircraft (h).
- $W^{\text{max}}, W_a^{\text{max}}$: Total fleet size limits and aircraft type fleet size limit.
- LF^{max}: Maximum load factor.
- $B_a^{\text{min/max}}$: Battery SoC limits for aircraft a (kWh).
- P_a^{charge}: Charging power of aircraft a (kW).
- T_{ra}^{FLIGHT}: Flight time of aircraft a on route r (h).
- $T^{\text{MIN,TURN}}, T^{\text{SETUP}}$: Minimum turnaround time and charging setup times (h).

To maintain cost structure consistency, both kerosene and electricity costs for a flight are calculated using the price at the destination airport.

3. Decision Variables

Core Decision Variables

- $w_a \in \mathbb{Z}_{\geq 0}$: Number of aircraft of type a acquired.
- $z_{ra} \in \mathbb{Z}_{\geq 0}$: Monthly frequency of aircraft a on route r.
- $c_{ra,k} \in \mathbb{R}_{\geq 0}$: Energy charged into aircraft a at stop k (kWh).
- $p_{ij} \in \mathbb{Z}_{\geq 0}$: Passengers transported on leg (i, j).

Auxiliary Variables

- $b_{ra,k} \in \mathbb{R}_{\geq 0}$: Battery level of aircraft a on arrival at stop k (kWh).
- $t_{ra,k} \in \mathbb{R}_{\geq 0}$: Turnaround time for aircraft a at stop k (h).
- $y_{ra,k}^{\text{charge}} \in \{0, 1\}$: Binary decision to charge aircraft a at stop k.

4. Constraints Explanation

The objective function and constraints are presented on the next page for readability, while this section explains the constraints.

The fleet size is limited by the total fleet cap in (2) and by type-specific limits in (3). Passenger flow on any given leg is capped by the available market demand (4) and the total capacity offered on that leg, adjusted by the maximum load factor (5).

Total monthly operating time for each aircraft type is constrained by available hours per aircraft multiplied by the fleet size. Kerosene aircraft block time ((6)) uses a fixed turnaround time for the $(N_r - 1)$ intermediate stops. For electric aircraft, the total block time ((7)) incorporates variable turnaround times $t_{ra,k}$, which are decision variables dependent on charging choices.

A final series of constraints governs electric aircraft operations. Constraint (10) models the energy balance across each stop of a route. To ensure operational continuity, (8) mandates that each route begins with a full battery, while (9) ensures the aircraft can be fully recharged upon returning to the hub. Constraints (11) and (12) enforce the minimum and maximum battery state-of-charge limits upon arrival and before departure at every stop, while (13) prevents charging before the first leg of a route.

The turnaround time for EA is determined by a minimum duration (15) and the charging time (16). To model the charging decision, a 'Big-M' constraint (14) links the continuous charge amount $c_{ra,k}$ to the binary decision $y_{ra,k}^{\text{charge}}$, using a tighter bound of $(B_a^{\text{max}} - B_a^{\text{min}})$ to improve solver performance.

5. Linearization and Solver Implementation

The formulation includes bilinear terms in the objective function (1) and block time constraint (7), resulting from the products of the integer flight frequency z_{ra} with the continuous charging energy $c_{ra,k}$ and turnaround time $t_{ra,k}$ variables. Since z_{ra} is an integer, these products can be exactly linearized using standard auxiliary variable techniques, ensuring the problem is mathematically equivalent MILP. We leverage the Gurobi optimizer's pre-solve capability to automatically linearize these terms, enabling the model to be solved to global optimality without requiring manual expansion of the auxiliary linearization constraints.

6. Objective Function

$$\text{maximize} \quad \sum_{(i,j)\in\mathcal{L}} Y_{ij}L_{ij}p_{ij} \qquad \text{(Revenue)}$$

$$- \sum_{a\in\mathcal{T}} C_a^{\text{fix}}w_a \qquad \text{(Fixed Costs)}$$

$$- \sum_{a\in\mathcal{T}} \sum_{r\in\mathcal{R}} \left(\sum_{(i,j)\in\mathcal{L}_r} C_a^{\text{op,ask}} S_a L_{ij} \right) z_{ra} \qquad \text{(Operating Costs)}$$

$$- \sum_{a\in\mathcal{T}_k} \sum_{r\in\mathcal{R}} \left(\sum_{(i,j)\in\mathcal{L}_r} F_{ij}^a P_j^{\text{kero}} \right) z_{ra} \qquad \text{(Kerosene Costs)}$$

$$- \sum_{a\in\mathcal{T}_e} \sum_{r\in\mathcal{R}} \left(\sum_{k=1}^{N_r} c_{ra,k} P_{A(r,k)}^{\text{elec}} \right) z_{ra} \qquad \text{(Electricity Costs)} \qquad (1)$$

7. Constraints

$$\sum_{a\in\mathcal{T}} w_a \leq W^{\text{max}} \qquad\qquad\qquad\qquad (2)$$

$$w_a \leq W_a^{\text{max}} \qquad\qquad \forall a \in \mathcal{T} \qquad (3)$$

$$p_{ij} \leq D_{ij} \qquad\qquad \forall (i,j) \in \mathcal{L} \qquad (4)$$

$$p_{ij} \leq LF^{\text{max}} \left(\sum_{r\in\mathcal{R}_{ij}, a\in\mathcal{T}} S_a z_{ra} \right) \qquad \forall (i,j) \in \mathcal{L} \qquad (5)$$

$$\sum_{r\in\mathcal{R}} z_{ra} \left(T_{ra}^{\text{FLIGHT}} + (N_r - 1)T^{\text{MIN,TURN}} \right) \leq Hw_a \qquad \forall a \in \mathcal{T}_k \qquad (6)$$

$$\sum_{r\in\mathcal{R}} z_{ra} \left(T_{ra}^{\text{FLIGHT}} + \sum_{k=1}^{N_r-1} t_{ra,k} \right) \leq Hw_a \qquad \forall a \in \mathcal{T}_e \qquad (7)$$

$$b_{ra,0} = B_a^{\text{max}} \qquad\qquad \forall r, a \in \mathcal{T}_e \qquad (8)$$

$$b_{ra,N_r} + c_{ra,N_r} = B_a^{\text{max}} \qquad\qquad \forall r, a \in \mathcal{T}_e \qquad (9)$$

$$b_{ra,k+1} = b_{ra,k} + c_{ra,k} - E_{A(r,k),A(r,k+1)}^a \qquad \forall r, a \in \mathcal{T}_e, k \in \{0,\ldots,N_r-1\} \qquad (10)$$

$$B_a^{\text{min}} \leq b_{ra,k} \leq B_a^{\text{max}} \qquad\qquad \forall r, a \in \mathcal{T}_e, k \in \{1,\ldots,N_r\} \qquad (11)$$

$$b_{ra,k} + c_{ra,k} \leq B_a^{\text{max}} \qquad\qquad \forall r, a \in \mathcal{T}_e, k \in \{0,\ldots,N_r\} \qquad (12)$$

$$c_{ra,0} = 0 \qquad\qquad \forall r, a \in \mathcal{T}_e \qquad (13)$$

$$c_{ra,k} \leq (B_a^{\text{max}} - B_a^{\text{min}})y_{ra,k}^{\text{charge}} \qquad \forall r, a \in \mathcal{T}_e, k \in \{1,\ldots,N_r\} \qquad (14)$$

$$t_{ra,k} \geq T^{\text{MIN,TURN}} \qquad\qquad \forall r, a \in \mathcal{T}_e, k \in \{1,\ldots,N_r-1\} \qquad (15)$$

$$t_{ra,k} \geq \frac{c_{ra,k}}{P_a^{\text{charge}}} + T^{\text{SETUP}}y_{ra,k}^{\text{charge}} \qquad \forall r, a \in \mathcal{T}_e, k \in \{1,\ldots,N_r-1\} \qquad (16)$$

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III. Data and Model Parameters

This section outlines the primary data sources and key model parameters with a comprehensive description provided in Appendix A.

1. Aircraft Specifications

The study evaluates the conceptual Elysian E9X-440 electric aircraft and the kerosene-fueled Embraer ERJ-175, a comparable kerosene aircraft in terms of passenger capacity and operated in the KLM cityhopper fleet [62] and in previous EA research [63, 64]. For battery safety, the E9X limits its battery SoC to between 10 and 95% [65]. Furthermore, non-energy costs are split into fixed costs, linearly depreciated from the estimated new acquisition price over 25 years [66, 67], and auxiliary operating costs, simplified to a single cost per seat-km flown. Detailed aircraft specifications are provided in Appendix A. To model an early-stage adoption, the fleet is capped at 10 aircraft. This constraint forces the model to prioritize the highest-yield routes over simply servicing all profitable ones. While the model can deploy fewer aircraft, full utilization is expected. Lastly, a minimum turnaround time of 30 minutes is maintained for both electric and kerosene aircraft, aligning with low-cost carrier (LCC) targets [68, 69]

2. Market Data

Monthly point-to-point (P2P) passenger demand for intra-European travel (2015–2024) is constructed by joining per-airport departure data sourced from Eurostat [70]. The data counts transfer passengers for each leg they fly, allowing the model to capture multi-leg traffic implicitly through observed P2P demand. Post-Brexit demand data is missing but is reconstructed by mirroring incoming demand flows, a choice validated in Appendix A. Furthermore, a 10% market share limit applies per leg, and passenger capacity is capped at the EU27 mean load factor for 2015–2024 of 78.6% [70]. Lastly, yields (€/pax-km) are estimated using a scaled distance-based curve from Justin et al. [1], calibrated against flight fares for 206 European routes scraped from Google Flights (shown in Figure 2) and are scaled monthly using the Harmonized Index of Consumer Prices (HCIP) airfare index to account for seasonal variation [71].
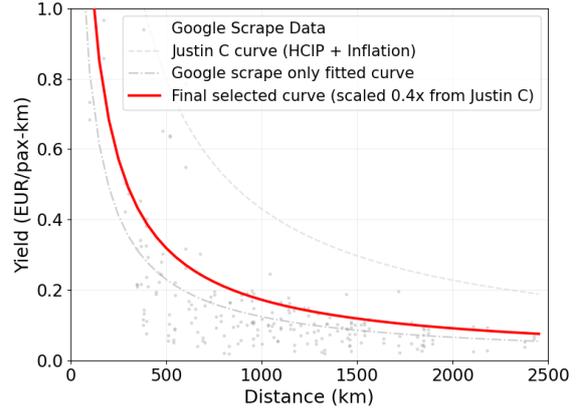
Figure 2. Distance-to-Yield Curve Calibration. Plot showing yield per passenger-km against flight distance. Comparing Google Flights data (grey dots) with the yield curve from Justin et al. [1], resulting in the adapted curve (red) used in this research.

3. Network Structure

The European network is centered on Amsterdam Schiphol (EHAM) as the hub because Elysian Aerospace, the manufacturer of the case study aircraft (the E9X), is headquartered there. A sensitivity analysis on the hub selection is presented in Appendix G. The network comprises 115 large European airports from the OurAirports database [72]. Great-circle distances between all airports are artificially extended by 7% to account for realistic flight paths [73].

4. Energy Prices

Monthly wholesale electricity prices at the country level are sourced from Ember [74]. A uniform 40% markup is applied to estimate the price airports pay, accounting for intermediary fees. This markup is derived by comparing wholesale data with end-user prices for large consumers (150+ GWh/year) from Eurostat [75]. Historical jet fuel prices are based on the United States Energy Information Administration (U.S. EIA) spot price [76] and a 10% markup to cover local logistics as recommended by an IATA representative [77]. Furthermore, a 10% minimum profit margin is applied to account for unmodeled costs and to exclude marginally profitable routes.

A. Key Performance Metrics and Time Periods

Financial performance is evaluated using total profit and energy costs. The stability of these metrics is measured using the Coefficient of Variation (CV), defined as the ratio of the standard deviation to the mean (CV = σ/μ). To normalize results for broader applicability, financial performance is sometimes expressed as a percentage of the maximum profit achievable under perfect foresight. Also note the distinction between electricity cost (total electricity cost paid by the airline to operate the entire network) and electricity price (price at a specific location).

Structural performance is assessed by analyzing operational decisions, including the number of routes flown, weighted average leg distance, total flight volume, fleet size, and route stability over time.

Furthermore, throughout this analysis, stability refers to the consistency of performance over time (measured by CV), robustness describes a plan's ability to perform well under modified inputs, and resilience measures the network's capacity to recover from external shocks.

Lastly, due to the significant impact of the COVID-19 pandemic, the analysis is segmented into four standard time periods. They are split by calendar year to ensure consistent month-to-month comparisons even though the pandemic's effects began in March 2020:

- **Pre-COVID:** January 2015 to December 2019
- **COVID:** January 2020 to December 2022
- **Post-COVID:** January 2023 to December 2024
- **Entire testing window:** Jan 2015 to Dec 2024

Pre and Post-COVID are also referred to as 'stable' time periods, and the COVID period as 'volatile'.

B. Electricity vs. Kerosene Prices

Before presenting the results, we begin by analyzing the energy price data used in our model. This tests our study's premise that electricity's volatility differs significantly from that of kerosene prices.

An analysis of Dutch prices from 2015 to 2024 reveals stark differences in volatility with other European countries showing similar trends. The CV of electricity prices is nearly triple that of kerosene (90.1% vs. 32.9%), and the average change in price from one month to the next is substantially higher for electricity (14.0% vs. 8.2% for kerosene). As shown in Table 3, electricity prices also exhibit more frequent large price swings. These differences in volatility underscore the need for an updated planning approach for electric aviation.

Table 3. Frequency of significant monthly price changes for kerosene and electricity (2015–2024)

Threshold	Kerosene	Electricity
>10%	36 months	64 months
>20%	6 months	27 months

IV. Results: Electric Fleet Operations

This section presents the results for the model using a European E9X-440 electric aircraft fleet operating from the Amsterdam Schiphol hub.

The analysis begins in section IV.A by evaluating the fleet's financial performance and cost structure. Section IV.B then examines the structural characteristics of the optimized network, detailing the route selection and flight frequency decisions. Finally, Section IV.C explores the optimal charging behavior, showing how accurate electricity prices can be utilized to make smarter strategic charging decisions. Detailed results are presented in Table 4 for three months selected to highlight both seasonal and yearly variations in performance.

A. Financial Performance

This section evaluates the E9X-440 fleet's profitability and costs to determine its financial viability.

1. Baseline Profitability and Revenue

The results show that a fleet of E9X-440 electric aircraft could have been operated profitably in the past 10 years. In 2024, the mean monthly operating profit of €5.59M, with the minimum of €3.76M, still provides a healthy profit in down seasons. Looking at the long-term trend shown in Figure 3, the same trend holds throughout the entire period, except for the three years of the COVID epidemic. Figure 3 shows profitability during COVID only because our analytical model can freely redesign the optimal network and fleet size each month, even shrinking to one aircraft. For a more realistic electric airline with fixed costs locked at the pre-pandemic level of ~€5M per month, the same period would have resulted in heavy losses for nearly three years.
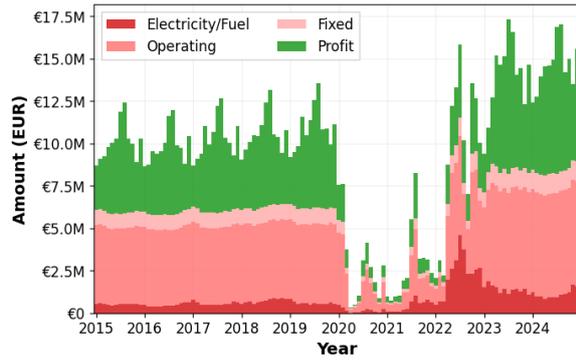
Figure 3. Monthly Breakdown of Revenue (2015–2024). Chart decomposing monthly revenue into operating costs, fixed costs, and net profit.

Table 4. Results for the E9X-440 fleet. Distances include a 7% route lengthening factor. Fleet size is fixed at 10 aircraft. Profit Optimality Gap of 0.1%.

Metric	Jun-23	Jan-24	Jun-24
Financial Performance			
Revenue [M€]	15.1	12.4	14.9
RASK [¢/skm]	23.4	18.8	23.0
Rev. per Pax [€/pax]	121	101	120
Total Cost [M€]	8.71	8.65	8.27
Operating Cost	6.15	6.28	6.17
Fixed Cost	1.16	1.16	1.16
Electricity Cost	1.40	1.22	0.940
CASK [¢/skm]	13.5	13.1	12.7
Cost per Pax [€/pax]	69.9	70.3	66.5
Op. Profit [M€]	6.41	3.77	6.64
Profit Margin [%]	42.4	30.4	44.5
Operational Statistics			
Demand Served [kpax]	125	123	124
Freq. (Min–Max) [flights]	1–47	1–51	2–48
Routes Flown	643	626	663
Total Legs Flown	1760	1750	1760
Total ASK [Mseat-km]	64.7	66.1	64.9
Total RPK [Mpax-km]	50.9	51.8	51.0
Network & Geography			
Unique Routes (of 798)	44	46	43
Unique Legs (O-D)	79	83	78
Active Airports (of 115)	23	24	23
Avg Flight Distance [km]	408	421	410
Avg Leg Length [km]	367	375	368
Energy			
Mean Elec. Price [€/MWh]	130	119	109
Total Energy Charged [GWh]	10.8	11.0	10.8
Avg Energy/Charge [kWh]	7840	6750	8220

2. Cost Structure

Electricity's share of variable costs ranged from 5.1% to 53.9%, driven by price spikes during COVID. The pre-COVID share averaged 11.1% (7.3–16.1%), doubled to 22.6% (peak 53.9%) during the pandemic, and then settled back down to 17.1% (11.9–25.4%) afterwards. This highlights electric aviation's sensitivity to energy price fluctuations, though the absolute impact remains small compared to other operational expenses, as can be seen in Figure 3.

3. Financial Drivers of Planning Decisions

High passenger demand is the dominant factor in operational strategy, outweighing even extreme electricity costs. For example, in July 2022 (COVID), the model opts to operate a fleet of 6 aircraft, accepting an electricity price 6 times higher than before, resulting in almost 5.7 times higher electricity costs per aircraft. This demonstrates that high summer yields outweigh even extreme energy costs, showing the dominance of yield and demand in overall strategic network planning.

B. Structural Performance

Moving on to analyzing the network's structural performance, this section examines the decisions made by the network, including route selection, flight frequencies, and fleet sizing.

1. Route Selection

The model's route selection reveals a dual network structure: a stable operational core complemented by a large, transient set of opportunistic routes. Out of 239 unique routes flown in the 120 month time span, a core group of just 18 routes is flown in over 80% of the months and serviced an average of 49.6% of the total monthly demand. In contrast, the bottom 56% of all unique routes collectively serviced only 5.3% of monthly demand. As shown in Figure 4, these core routes comprise the 51 'Stable' legs that form the permanent backbone of the network, while the remaining opportunistic flying accounts for 125 'Unstable' legs. This finding points to a strategy centered on a robust core that acts as the network's workhorse, while maintaining optimality through a wide array of secondary routes.

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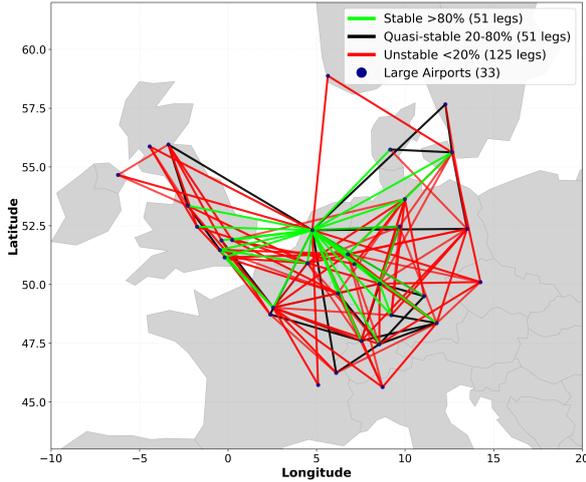
Figure 4. Leg Stability (2015–2024). Green lines represent stable routes (>80% of months), red lines represent unstable routes (<20% of months).

Further examination reveals that this stable core is predominantly composed of short, direct connections. During the 60-month pre-COVID period, direct routes remain actively flown almost twice as long as multi-stop routes (44.4 months vs. 24.4 months). They also handle significantly more traffic, with an average of 989 flights per route over that period, more than triple the 295 flights for multi-stop routes. Furthermore, the network's design prefers shorter routes, as seen by the mean flight distance in June 2024 being only 409 km, substantially less than the 850 km effective range of the E9X-440.

While resilient during periods of market calm, the network's core structure proves vulnerable to major external shocks. The number of flight legs active in 100% of the months plummets from a pre-COVID high of 53 to just 9. This dramatic reduction illustrates that the COVID market disruption is significant enough to force the airline to abandon even its most historically reliable connections, leading to a near-complete shift in the route portfolio and an increased reliance on transient, opportunistic flying to navigate the crisis.

To identify the drivers of route selection, we rank all potential routes using several metrics and observe where the model's chosen routes fall in these rankings. The analysis reveals that route distance is the single strongest predictor of selection. On average, the model's chosen routes rank in the top 20% of all routes, from shortest to longest. Route distance is an effective predictor because the inverse-distance yield curve dominates. On the other hand, mean

electricity prices along the route are not a good predictor, with a mean percentile of 43.1% (50% being equivalent to random).

In summary, the model builds a core of short, direct, high-frequency routes for their superior yield, lower energy costs, and higher asset utilization. This reveals that while electricity prices influence profitability, they do not noticeably drive route selection. The optimal network is a dynamic combination of this stable core and flexible, longer routes that shift during severe market disruptions.

2. Flight Frequency and Fleet Size

Looking at the structural performance in the flight frequency and fleet size domain, we observe that the model actively reallocates flight frequency across the network from month to month. While total network flights may be stable, the model constantly reassigns flights among routes. We quantify this internal churn with mean monthly 'Route Frequency Reallocation': the percentage of monthly flights reallocated between routes from one month to the next. This metric reveals network adaptation to changing market conditions, even with constant overall flight frequency. Table 5 illustrates this. During the stable pre-COVID era, overall network flight volume varied by only 2.4% month-to-month, while the internal reallocation rate was 12.7%.

Table 5. Comparison of network flight frequency volatility (CV) and mean route frequency reallocation across different periods (2015–2024).

Period	Total Freq. CV (%)	Route Freq. Reallocation (%)
Pre COVID	2.4	12.7
COVID	73.4	41.8
Post COVID	5.4	14.6

As for fleet size, the full fleet is typically employed, showing sufficient profitable demand, with only the COVID pandemic grounding all but one aircraft.

C. Charging Performance

This paper examines how traditional strategic airline planning problems can be adapted to better suit electric aircraft by incorporating accurate electricity prices and expanding the planning problems addressed. One expansion this paper recommends

is the inclusion of strategic charging decisions, enabling the model to optimize charging amounts at each airport, an opportunity made possible by the incorporation of accurate spatially distinct electricity prices. This section examines the charging decisions made by the STTEAP model, categorizes the optimal behaviors observed, and analyzes the underlying financial and operational trade-offs.

1. Optimal Charging Behavior

The model's charging strategy is defined by *charging decisions*: the predetermined amount to charge at each intermediate stop for a given route. For example, in June 2024, the model selects 9 two-leg routes and 35 three-leg routes, totaling 79 unique charging decisions. Each time a route is flown, these decisions result in *charging events*. The total number of events is the sum of decisions scaled by their respective flight frequencies.

These events are categorized by location (final hub or intermediate stop), charge amount (full, partial, or no charge), and charging strategy, of which we define three, although more exist:

- **Changing to Min:** Charging the minimum amount needed to fly the next leg
- **Charge Ferrying:** Charging more energy than required for the next leg, including charging to full and partial charging
- **No Charge:** Skipping charging at an airport

The model employs a complex charging strategy that a single rule, such as always charging to full, cannot replicate. The distribution of charging events by these categories for the post-COVID period is shown in Figure 5, with the whole time period showing similar proportions (shown in Appendix C). Note that the largest category, "Final Charge to Full" (37.1%), is dictated by a model constraint (9) for state continuity and is thus not a strategic decision.

Aside from "Final Charge to Full", the most common choice is to ferry electricity. This approach, combining charging to full (22.2%) and partial ferrying (7.5%), accounts for 29.7% of all charging events. When considering only the strategic decisions at intermediate stops, ferrying represents nearly half (47.2%) of all charging events. In the vast majority of these cases, the model charges to full, indicating that whenever it is profitable to ferry extra energy, it tends to take as much as it can.
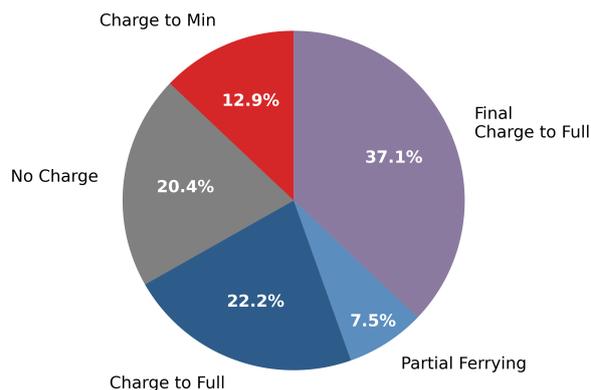
Figure 5. Charging Events Distribution (Post-COVID, 2023–2024).

The second most frequent decision is to not charge at all (20.4%). This is possible because the aircraft's effective range of 850km is more than double the average ~400km route selected by the model. This strategy is notable because skipping charging actually slightly increases the total time of a route. The minimum turnaround time of 30 minutes, with the 15-minute setup and teardown time, means that the aircraft can always charge for the remaining 15 minutes without increasing the turnaround time. Not doing so means that it will have to charge 15 minutes longer at another stop. Therefore, skipping charging is a decision driven purely by the goal of minimizing electricity costs. This indicates that sometimes not charging at a specific expensive airport is less costly than forgoing the potential revenue from flying slightly more frequently that month.

The third major strategy is to charge only the minimum energy required for the next leg (12.9% of events). This approach is typically employed to minimize cost exposure at airports with expensive electricity, ensuring the aircraft has just enough energy to reach a cheaper charging location. Combined with charge ferrying, this demonstrates that the model actively accounts for electricity prices in the charge decision space.

2. In-Depth Charging Analysis of One Month

Diving into one month, June 2024, a detailed look at all 79 unique charging decisions for all intermediate stops, shown in Figure 6, reinforces these distinct patterns. The y-axis represents the battery's SoC for each decision. In the stacked bar plot, the light grey area shows the minimum required SoC, while the darker grey area represents the battery state before

the charging event. The purple line indicates the battery state required to fly the next leg, and the green bar shows the amount charged.

Figure 6 visually confirms the findings in Figure 5, showing that partial charging is relatively uncommon, with decisions heavily skewed toward either charging to full or not charging at all. We also observe four instances where an aircraft initiates the charging event at the absolute minimum SoC, indicating that the model deliberately optimizes the preceding leg to arrive empty of usable charge. This allows the aircraft to maximize charging at the airport, which it proceeds to do in all four cases.
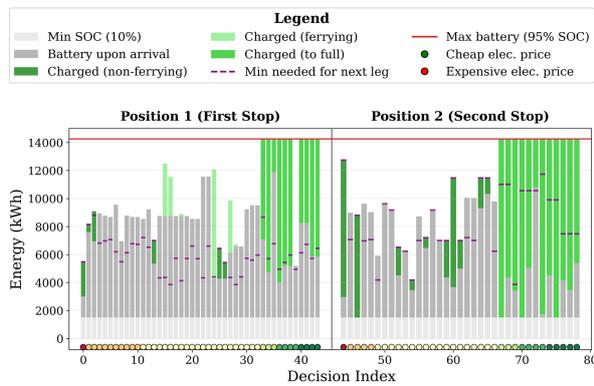
Figure 6. Detailed Charging Decisions at Intermediate Stops (June 2024). Bar chart of 79 charging events sorted by electricity price, showing battery state upon arrival (grey), energy added (green), and minimum required energy (purple line).

3. Charging Strategy Simplifications

The preceding analysis shows that many optimal decisions align with simple heuristics: charging to the maximum or charging to the minimum. This raises a practical question: could a single, fixed charging rule be applied universally to simplify the planning model? Such an approach is common in academic literature and could reflect operational policies. For instance, always charging to the maximum SoC provides a larger safety buffer. This section quantifies the financial cost of enforcing such simplifications. We consider two simplfied strategies:

- MAX_E: Enforces a full charge to the maximum allowable SoC at every stop
- MIN_E: Permits charging only the minimum energy essential for the subsequent leg

The results in Table 6 show that both simplifications lead to a tangible profit reduction of approximately 1%. The MAX_E strategy forces unnecessary charging at expensive electricity locations, increasing total electricity costs by 7.96%. Conversely, the MIN_E strategy, while seemingly more cost-conscious, still increases electricity costs by 6.96%, likely by shifting the charging burden to more expensive hub airports and potentially extending route times, indirectly reducing revenue potential.

Table 6. Financial impact of constrained charging strategies relative to the fully optimized baseline (2015–2024)

Strategy	Profit Impact	Elec. Cost Impact
MIN_E	−0.98%	+6.96%
MAX_E	−1.12%	+7.96%

Interestingly, the relative performance of these simplified strategies does not correlate with their frequency in the optimal solution. Although ferrying (which involves charging to maximum) is the most common strategic choice in the optimal model (29.7% of events), forcing this strategy everywhere (MAX_E) yields a worse financial outcome than forcing the less common minimum-charge strategy (MIN_E, 12.9% of events). This highlights that the value lies not in a single 'best' rule, but in the flexibility to apply the right rule in the correct context.

In conclusion, the optimal charging strategy is not a single rule but a dynamic balance of competing behaviors. The model demonstrates sophisticated multi-leg optimization, at times deliberately arriving at a stop with minimal energy to maximize uptake from a cheap electricity source. This confirms that profitability in an electrified network is unlocked not by a fixed heuristic, but by a flexible, context-aware charging policy. The value lies not in a single 'best' rule but in the flexibility to apply the right one in the right context. While the ~1% profit impact seems modest, it confirms the benefit of an integrated, context-aware charging policy.

V. Results: The Value of Price Information

The previous section showed that spatiotemporal electricity prices can impact the bottom line and drive the charging behavior. This section now quantifies the financial value of this information on the

entire network's plan. We measure the penalty, in terms of lost profits and excess electricity costs, that arises when planners rely on simplified price assumptions common in the literature, such as yearly or network-wide averages.

All experiments follow the same plan-then-re-evaluate methodology: a network plan is optimized using imperfect price information of varying quality, re-evaluated using the true high-resolution prices, and compared to the perfect-information benchmark. The resulting profit gap defines the Value of Knowledge (VoK) lost due to imperfect information.

We decompose this VoK along three dimensions of electricity price data:

A. **Price Awareness:** The benefit of using any price signal versus assuming electricity is free
B. **Price Magnitude:** The sensitivity of planning outcomes to errors in the absolute level of prices
C. **Temporal Granularity:** The impact of using less granular temporal data (quarterly or annual) prices instead of monthly prices

Note: For all experiments in this section, the minimum route profit-margin constraint is relaxed from 10% to 0%. This ensures the feasibility of plans generated under highly distorted price signals.

A. Value of Knowing it At All: The Benefit of Price Awareness in Planning

This section compares the performance of a planner with perfect price information against two common, simplified price information strategies, hereafter referred to as the *alternative* strategies:

- **Perfect:** The model uses the unmodified, high-resolution electricity price data
- **Agnostic:** The model assumes electricity is free, equivalent to setting the mean price to zero
- **Average:** The model uses a network-wide average price, equivalent to setting the variance to zero

The results in Table 7 show that under stable market conditions, both alternative strategies perform remarkably well, achieving 99.2% of the optimal profit, and increasing electricity costs by 5.4%. While the performance can be erratic, with profit losses sometimes reaching 2.5% (Figure 7), the small average loss suggests that network design is mainly driven by other larger factors such as yield and demand. The key difference emerges in volatile markets. The average price model prevents major losses because

Table 7. Financial performance of planning models using imperfect price information, relative to a perfect information benchmark (2015–2024)

	Avg. Price	Agnostic
Pre-COVID Period (Stable Prices)		
Profit	99.2%	99.2%
Electricity Cost	105.8%	105.6%
COVID Period (Volatile Prices)		
Profit	97.3%	64.8%
Electricity Cost	105.7%	165.3%
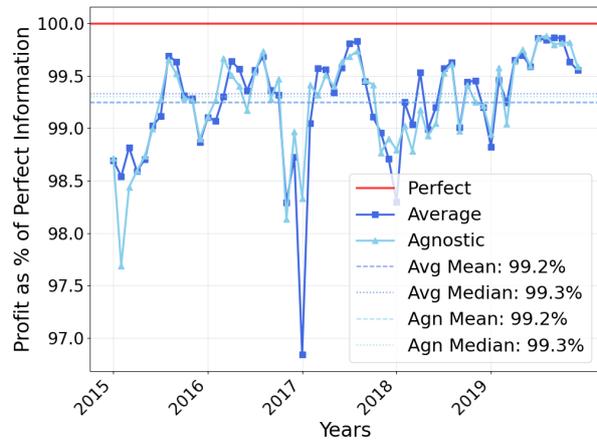
Figure 7. Pre-COVID (2015–2019) Mean Relative Profit Performance. Line chart comparing the relative profit of Average Price and Agnostic planning models against a perfect information benchmark.

the uniform price acts as a global cost floor. This raises the minimum profitability required for any route, preventing the planner from selecting flights that have become excessively unprofitable due to high electricity prices. In contrast, the agnostic strategy lacks this indicator, resulting in a profit that plummets to 64.8% of the profit achieved with perfect information. The value of incorporating average electricity prices thus lies in more accurate global cost estimations and, from a network design perspective, in risk mitigation.

The near-identical performance of the agnostic and average price models in stable conditions stems from a common simplification: both eliminate spatial price variation. Without price differences between airports, the optimizer lacks a cost signal to favor one charging location over another. This explains why the profit loss of the agnostic model is not regained

by adding an average price. Recovering this loss requires granular spatial price information. Indeed, the profit loss from using a uniform average price is almost completely eliminated by reintroducing just 10% of the true spatial price variance. This small signal is sufficient to correctly rank airport prices, guiding the optimization to a near-optimal solution (0.02% profit loss). This demonstrates that the model is highly sensitive to the correct price ranking but robust to the magnitude of the differences.

Analysis of the model's charging decisions confirms how this lack of a price signal impacts behavior. When run with uniform electricity prices, the complex charging logic described in section IV.C simplifies to a binary choice of either charging to maximum SoC or not charging at all. Consequently, the average price acts merely as a fixed operational cost rather than a dynamic variable that alters network structure. This suboptimal charging behavior also increases total electricity costs. The 0.8% profit loss is proportional to the roughly 1% losses for strategies that always charge to the minimum or maximum. The model performs slightly better because having the flexibility to choose whether to charge to full or not to charge at all beats a rigid strategy like MAX_E, which offers only a single option. The financial value of accurate price information (VoK) is thus likely primarily driven by the ability to optimize these strategic charging decisions, though quantifying the precise division between network effects and charging effects requires further research.

B. Value of Knowing How Much: The Sensitivity of Planning to Price Magnitude

The next step is to quantify the value of knowing the magnitude of electricity prices. To achieve this, we generate network plans using uniformly scaled electricity prices (from 0x to 5x) and then re-evaluate the true profit and cost of those plans against the unmodified prices. The multiple by which the electricity price is increased is referred to as the *Electricity Price Markup Scaler*. A 5x multiple is not quite realistic (although 6x is seen during the worst of COVID), but it does help us understand the pattern in the behavior of a strategic electrified network under modified electricity prices.

In addition to helping us assess the importance of

electricity magnitude information, this experiment also provides a more practical insight into the damaging consequences of over- or underestimating electricity prices. When planning a strategic network many months to years in advance, planning must take into account uncertain estimates for electricity prices. This experiment simulates the impact of forecasting errors by examining what happens when an airline plans its network based on over- or underestimating electricity prices.

1. General Robustness with a High-Stakes Risk

The full 120-month analysis reveals a story of general robustness but with moments of extreme fragility. Figure 8 shows the profit achieved by plans based on overestimated electricity prices, compared to a plan with perfect information (the 1x multiple).

As shown in the figure, the median (blue horizontal line in each blue box) profit remains remarkably high even when prices are overestimated by a factor of four, indicating that typical network plans are not very sensitive to price magnitude. Beyond this 4x threshold, the bottom inner quartile of months begins to spread out and diminish quickly.

However, the mean performance tells a different story from the median. In certain volatile months, the system is exceptionally fragile, and even a moderate overestimation can cause profits to collapse to as low as 20%. This demonstrates that, while the system is robust on average, it is prone to catastrophic failure under specific conditions, posing a risk to electric airlines.
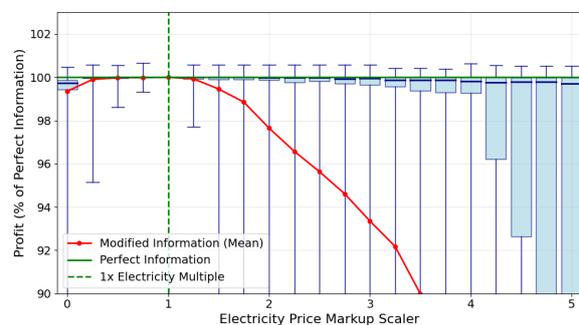
Figure 8. Relative Profit Loss over Electricity Price Markup (2015–2024). Box plots displaying profit retained relative to a perfect forecast when prices are adjusted by factors of 0x to 5x.

2. The Asymmetric Risk of Forecasting Errors

Our analysis reveals that overestimating electricity prices is more damaging to profitability than underestimating them. Overestimation acts as a contracting force, compelling the planner to prematurely cut marginally profitable routes and frequencies that would have remained profitable under the true prices. In contrast, the penalty for underestimation is consistently less severe, with the loss incurred by a flight with higher-than-expected electricity costs usually smaller than the profit lost by not flying the flight.

The financial impact of this asymmetry depends on the time period. During the stable, low-price pre-COVID period, forecasting errors had a negligible effect on profit. However, during the high-price COVID period, a 50% overestimation (1.5x multiple) reduces mean profit to 98.1%, whereas a 50% underestimation (0.5x multiple) retains 99.0% of the optimal profit (Table 8). Although these profit reductions appear nominal, they represent a significant deviation given the narrow margins inherent to this analysis.

Table 8. Mean profit loss resulting from underestimation and overestimation of electricity prices (2015–2024)

Scenario	Pre-COVID (% Profit)	COVID (% Profit)
Underestimation		
0.9x (-10%)	~100%	~100%
0.5x (-50%)	~100%	99.0%
Overestimation		
1.5x (+50%)	~100%	98.1%
2.0x (+100%)	~100%	92.1%

The takeaway for planners is that forecast accuracy is critical only during periods of high and volatile electricity prices. In such environments, where precise forecasts are difficult, our results suggest that a slight underestimation is the safer strategic bet. The financial penalty of paying more for electricity on a profitable network (the risk of underestimation) is far smaller than forgoing that profit by cutting routes (the risk of overestimation).

A key consideration is the underlying base effect: the high absolute prices during the COVID period amplify the financial impact of any percentage-based forecasting error. This design is nonetheless relevant, as real-world forecast uncertainty tends to scale with price magnitude. Thus, a relative error remains a suitable proxy for the proportional risks faced by planners in such high-stakes environments.

C. Value of Knowing When: The Significance of Temporal Granularity in Planning

This section assesses the value of temporal forecast granularity. We optimize network plans using price forecasts averaged over different horizons (quarterly, bi-annual, and annual) and then re-evaluate their performance against actual monthly prices. This approach quantifies the profit loss from using less temporal detail in strategic planning. The results are presented in Table 9.

The findings show that strategic network plans are remarkably robust to coarse temporal forecasts, particularly in stable markets. During the pre-COVID period, the mean profit loss is negligible (~0%) across all time horizons, and even the worst-case loss from using an annual average is less than 0.2%.

The key challenge emerges during volatile periods. While the average performance remains strong (a modest 0.7% mean loss for annual forecasts), using coarse data introduces significant tail risk, with single-month losses reaching 12%. This overall robustness stems not from predicting exact price levels but from correctly ranking airports according to their electricity prices. If this ranking holds, the plan remains close to optimal.

Table 9. Impact of temporal forecast granularity on mean and worst-case network profit (2015–2022)

| Months | Pre-COVID | | COVID | |
	Mean (%)	Worst (%)	Mean (%)	Worst (%)
1	0	0	0	0
3	~0	< 0.2	~0	< 0.2
6	~0	< 0.2	< 0.2	< 1.5
12	~0	< 0.2	< 0.7	< 12.0

Mean: Mean Profit Loss & Worst: Worst-Case Loss

To verify this, we analyzed the stability of the airport price ranking using Spearman's rank correlation. This method measures how consistently the order of airports from cheapest to most expensive stays the same over time, where a score of 1.0 indicates

a perfectly stable ranking and 0 indicates no relationship. The analysis confirms our hypothesis: a high month-to-month correlation of 0.81 shows the ranking is stable enough that a quarterly average remains an effective forecast. In contrast, the lower 12-month correlation of 0.59 reveals the ranking changes too much over a year, accounting for the degraded performance of annual forecasts. This rank instability was particularly evident during the volatile COVID period, when the 12-month correlation plummeted to 0.50, coinciding with severe outlier losses.

In summary, during stable markets, annual price averages are sufficient for robust planning. However, when markets become volatile, shifting to at least a quarterly forecast is a critical, low-cost strategy to mitigate severe outlier profit losses.

D. Order of Informational Value for Planners

Summarizing the findings, an order of informational value for network planning emerges, driven primarily by the need to mitigate risk in market volatility.

A. **Spatial Price Ranking** is most important. While ignoring spatial differences reduces profits by 0.8–2.7%, capturing the relative ranking of airports secures nearly all potential gains.

B. **Price Magnitude** is key for risk management. During volatile periods, overestimation can collapse profits to 20% of the optimal value, making accurate magnitude forecasting essential.

C. **Temporal Granularity** is the least sensitive dimension. Quarterly forecasts incur negligible penalties, and even coarse annual averages typically cause only a 0.7% loss.

VI. Results: Mixed Fleet Strategy

Having established the value of price information for strategically optimizing an electric fleet, we now turn to the final strategic planning problem that the model has not yet been allowed to vary: fleet composition. This unlocks a powerful new optimization lever. A mixed fleet can outperform a homogeneous one by acting as an inherent hedge against price volatility, enabling arbitrage across the energy markets for electricity and kerosene. Consequently, the central question becomes: *can a unified fleet-planning approach that integrates both aircraft types outperform a pure fleet in terms of profitability, stability, or both?*

Our analysis proceeds in three stages:

1) **Homogeneous Fleets** (Section VI.A) establishes baseline performance for a homogeneous electric versus a kerosene fleet, laying the groundwork for the mixed-fleet analysis.

2) **Unconstrained Mixed Fleets** (Section VI.B) explores the theoretical ceiling of flexibility by allowing the model to dynamically optimize the electric/kerosene fleet blend each month, revealing the ideal adaptive strategy.

3) **Constrained Mixed Fleets** (Section VI.C) evaluate the pragmatic reality of fixed fleet commitments, analyzing various electrification ratios to deliver a risk–return efficient frontier and practical strategic guidance.

A. Homogeneous Fleets

This section benchmarks four uniform fleets of electric E9X-440 or kerosene-powered ERJ-175, A320-200, or B737-800 aircraft.

1. Comparative Analysis of All 4 Fleets

The results in Figure 9 show four key findings.

First, a clear split in profit performance exists between the E9X and ERJ versus the A320 and B737. Despite fewer flights and higher total costs, the A320 and B737 greater passenger capacity generates higher revenue, driving healthier profits.

Second, the profit of the E9X and ERJ is remarkably similar. This demonstrates that electric aircraft can be competitive in the right operational landscape.

Third, kerosene aircraft recover roughly a year faster from the COVID pandemic. This divergence results from asymmetrical energy prices, with electricity prices spiking 2156% compared to just 651% for kerosene, as shown in Figure 10. While the demand collapse affects both, the electric fleet faced a compounded setback from the subsequent energy price shock.

Finally, a general trend across all fleets shows a slight increase in weighted-average leg distances post-COVID, indicating a shift toward a new equilibrium network after the COVID period.
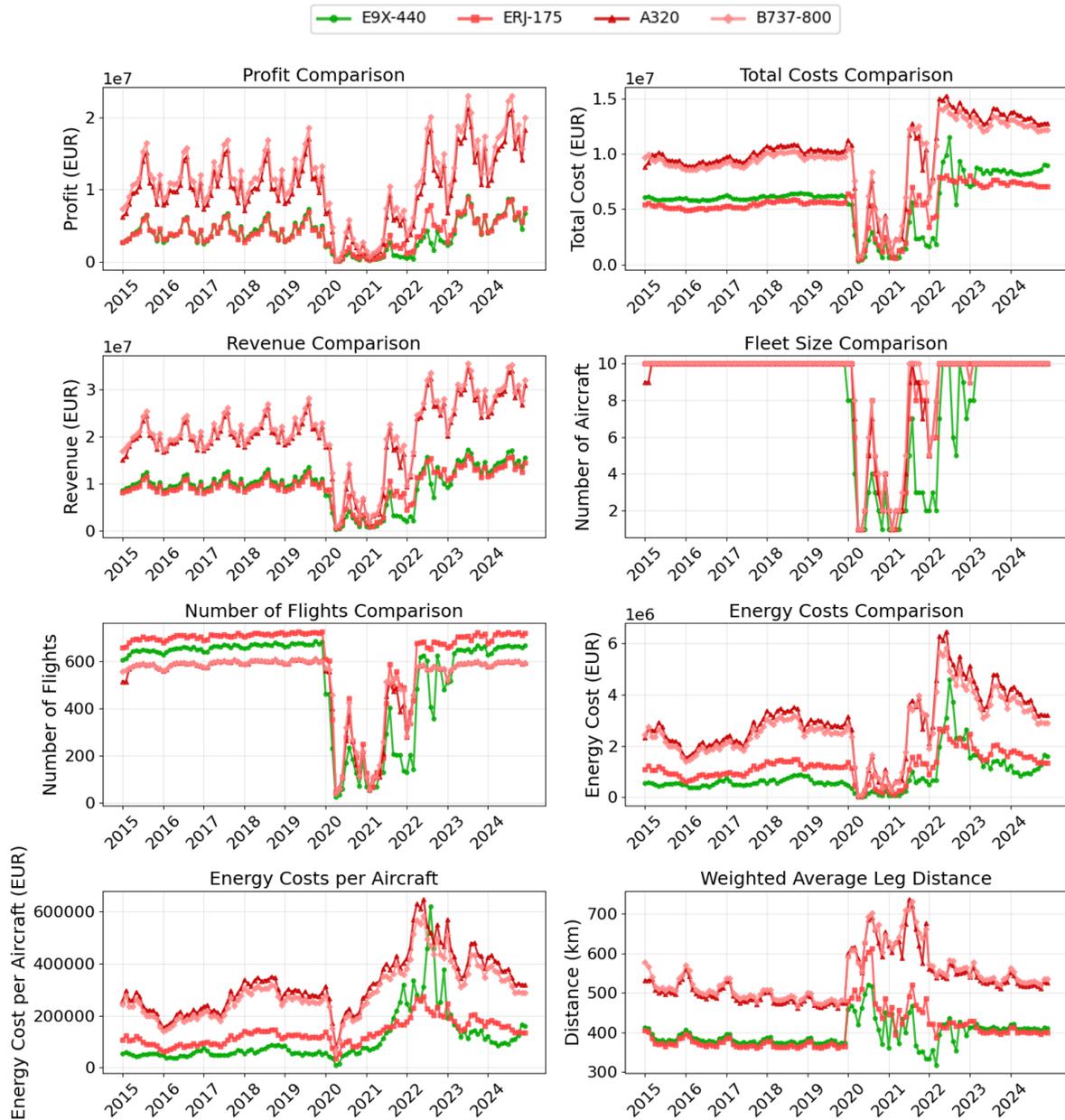
Figure 9. Performance of Uniform Fleets (2015–2024). Dashboard comparing financial and operational metrics for homogeneous E9X-440, ERJ-175, A320, and B737 fleets.
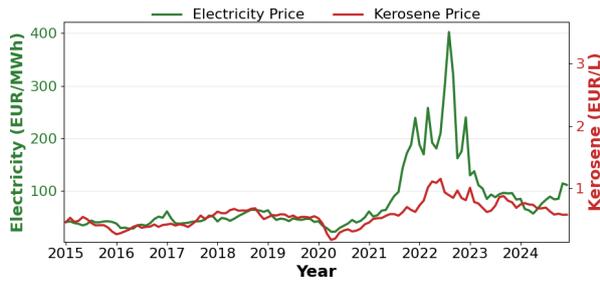
Figure 10. Energy Prices (2015–2024). Comparing price trends of EU-wide average wholesale electricity (green) and kerosene prices (red).

2. E9X-440 vs. ERJ-175 Performance

The total profits of the E9X-440 and ERJ-175 are comparable but stem from different strategic profiles. The comparison yields three lessons regarding the trade-offs required to operate an electric fleet.

First, the electric fleet (E9X) achieves near profit parity with the conventional ERJ-175 in stable markets by trading operational efficiency for energy savings. The E9X's substantial energy savings (€536k) and larger capacity (90 vs. 78 seats) offset its higher operating costs, slower speed, and 10% reduction in flights. Consequently, while the ERJ-175 was 6.4% more profitable over the decade, profit leadership was nearly even during the stable 2015-2019 period (E9X led for 30 months vs. the ERJ's 27).

Second, comparing the two fleets shows that financial stability is fragile due to exposure to energy-market volatility. Although electric energy costs are lower on average, they exhibit nearly triple the variance of kerosene (CV 88.5% vs. 35.5%) as seen in Table 10. Consequently, the E9X suffers from higher profit volatility (CV 57.1% vs. 49.9%).

Third, operational constraints force the electric fleet to adopt a distinct, high-commitment network strategy. The E9X maintains a rigid network footprint, showing very little fluctuation in the total number of active routes (CV 17.9%), whereas the kerosene fleet shows greater volatility (CV 37.3%). Consequently, individual electric routes are sustained for significantly longer periods (23.5 vs. 17.6 months).

B. Unconstrained Mixed Fleets

To explore the value of a mixed fleet, this analysis allows the SSTEAP model to pick between both the electric E9X-440 and the kerosene ERJ-175. For each month, the model calculates the optimal fleet composition, as well as the rest of the strategic net-

Table 10. Performance comparison of homogeneous electric (E9X) and kerosene (ERJ) fleets (2015–2024)

Metric	Kerosene (ERJ)	Electric (E9X)
Financial Risk		
Profit CV	49.9%	57.1%
Energy Cost CV	35.5%	88.5%
Network Stability		
No. of Routes CV	37.3%	17.9%
Avg. Leg Dist. CV	15.1%	9.7%
Total Flight Freq. CV	25.1%	34.7%
Route Lifespan		
Average Lifespan	17.6 mo	23.5 mo
Survival > 24 mo	18.1%	25.9%

Note: CV: lower = more stable

work decisions, such as routes and flight frequencies. The other reference aircraft (A320-200 and B737-800) are excluded as their superior performance characteristics prevent any mix with the E9X-440.

1. Financial Performance

Allowing the model to determine its fleet composition monthly resulted in an actively changing fleet composition, as shown in Figure 11. We observe periods of relatively evenly mixed fleets in 43 of the 120 months, demonstrating that the optimal strategy can sometimes be a mixed fleet one.
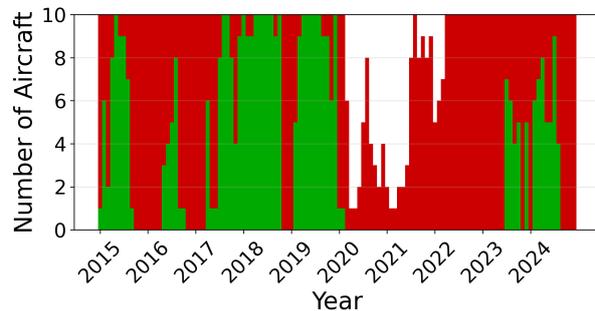
Figure 11. Optimal Unconstrained Fleet Composition (2015–2024). Stacked area chart showing the optimal mix of E9X-440 (green) and ERJ-175 (red) aircraft for a maximum fleet size of 10.

During periods of low electricity prices or high kerosene prices, the fleet composition heavily favors the electric E9X-440. Conversely, during COVID,

the model switches to a 100% kerosene ERJ-175 fleet to avoid the high cost of electricity. This ability to pivot acts as a natural hedge, shielding the airline from the extremes. Furthermore, when the optimal mix ratio switches, it often takes about two to three months to do so, indicating that a more gradual shift in the underlying environment is occurring. Lastly, even when one aircraft type dominates, the model often retains a small sliver of the other type, indicating that certain niche routes are profitable enough to justify a single aircraft.

The primary advantage of the mixed fleet is its ability to generate superior profits by leveraging the strengths of each aircraft type. The dynamically mixed fleet achieves a mean monthly profit of €4.1 million (2015–2024). This represents a significant 9.2% increase over the E9X-440-only fleet and a 2.6% improvement over the already competitive ERJ-175 fleet. The flexibility to adapt the fleet composition monthly between the E9X-440 and the ERJ-175 delivers these performance gains.

A better comparison would be to compare the idealized mixed fleet against the best homogeneous fleet for each month, since the model can always choose to become either homogeneous fleet itself. Crucially, in 16.7% of months, the mixed fleet achieves meaningful profit improvements exceeding 0.1%, with a mean profit advantage of 0.46% and a maximum additional gain of 1.5%. This shows that a mixed fleet can be more valuable than its parts. While this operational optimization appears modest, these margins are significant in airline operations and represent valuable efficiency gains. The remaining months show negligible differences, indicating the optimal strategy was either homogeneous or offered only marginal mixed-fleet gains.

A crucial finding is that this increased profitability does not come at the cost of stability. The mixed fleet's profit CV is 50.3%, comparable to the kerosene-only fleet's 49.9% and an improvement over the highly volatile pure electric fleet, which had a CV of 57.1%. The mixed fleet strategy captures the profit potential of electric aviation while preserving the financial stability of a kerosene fleet.

2. Structural Performance

The mixed-fleet optimization results in a complex aircraft assignment rather than a simple split based on range. This is evident in the flight distribu-

tion by leg distance (Figure 12), which shows both the E9X-440 and the ERJ-175 operating frequently on short-haul routes (200-800 km). Consequently, there is no distinct cutoff where electric aircraft exclusively handle short-haul missions. This operational complexity is further visualized in the network map (Figure 13), which displays significant route overlap between the two aircraft types.
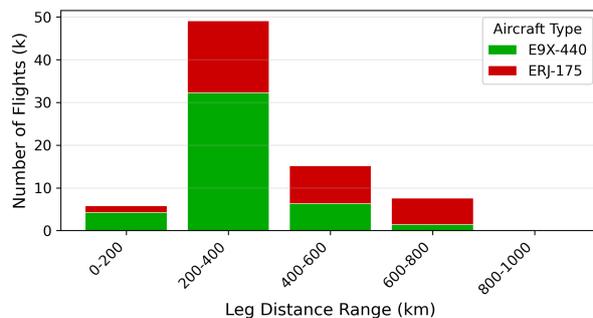
Figure 12. Flight Leg Distance Distribution by Aircraft Type (2015–2024). Histogram comparing flight distances of routes served by electric (green) versus kerosene (red) aircraft in a mixed fleet.
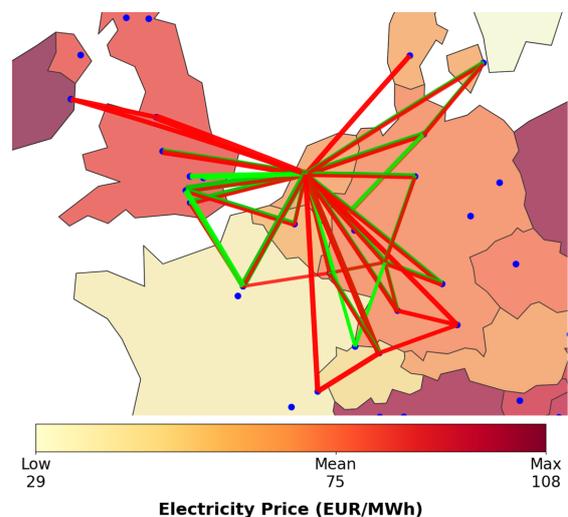
Figure 13. Mixed Fleet Network Map (June 2024). Geographical representation of a 50:50 mixed fleet, with electric routes in green and kerosene routes in red, overlaid on an electricity price heatmap.

3. Drivers of Fleet Electrification

Observing that the mixed-fleet composition shifts dynamically over time, this section investigates the primary driver of these changes. The central hypothesis is that energy prices govern fleet electrification. It is expected to increase when electricity is cheaper

than kerosene and decrease when it is more expensive. The following analysis tests this relationship.

To measure this more precisely, we define the kerosene-to-electricity price ratio (kerosene per liter price divided by electricity per kWh price). Figure 14 shows electrification against this ratio across all 120 months. Note that the y-axis shows the fleet's electrification ratio as a percentage, calculated by dividing the number of electric aircraft by the total number of aircraft in the fleet. In the plot, a sharp transition emerges: below 0.68, the fleet is almost fully kerosene; above 1.07, it is nearly all electric, with the steepest shift around 0.9. This narrow band defines the conditions under which a mixed fleet is optimal and can serve as an estimator of its effectiveness in future price environments. While the plot reveals a strong correlational pattern, it does not definitively establish causation. Further research using controlled price scenarios would be required to confirm this causal relationship.
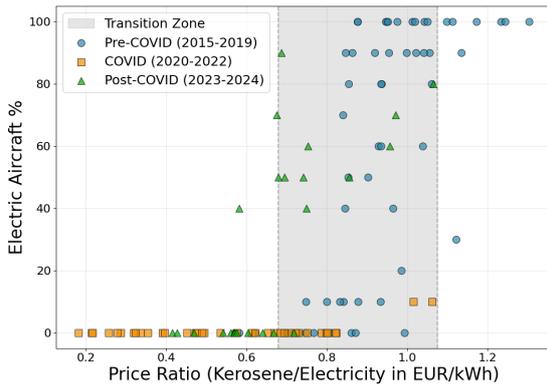
Figure 14. Fleet Electrification vs. Kerosene-to-Electricity Price Ratio (2015–2024). Plot showing fleet electrification percentage as a function of the energy price ratio. Each point represents a unique fleet composition in a specific month. The price ratio is dimensionless, with kerosene prices per liter converted to per-unit energy (9.58 kWh/L [2]).

4. Mixed Fleet vs. Conventional Fleet Assignment

To verify if the observed benefits arise from mixed-fleet assignment or are merely efficiency gains by allowing the model to select between two aircraft, as in standard fleet assignment, we conduct a control experiment. We introduce a hypothetical kerosene-powered version of the E9X with the same statistics as the electric version and an identical fuel effi-

ciency to the ERJ-175. The result of the control experiment is decisive: the model selects a homogeneous ERJ-175 fleet in all 120 months. This proves the mixed-fleet advantage stems not from operational differences like range or capacity, but from energy arbitrage between the decoupled electricity and kerosene markets.

The unconstrained analysis reveals a clear strategic path forward: the mixed-fleet model offers airlines a promising way to begin electrification. By combining electric and kerosene aircraft, an airline can slightly increase profitability compared to operating either fleet type in isolation. More importantly, this strategy provides a hedge against the extreme energy price volatility that makes a pure electric fleet a high-risk proposition today. The ability to dynamically allocate aircraft based on market conditions allows the airline to leverage the low operating costs of electric aircraft when favorable, and fall back on the reliability and flexibility of kerosene aircraft when necessary, increasing both profits and stability.

C. Constrained Mixed Fleets

While section VI.B demonstrated the benefits of unconstrained dynamic optimization, it provides limited data points and doesn't capture the risk and opportunity in a committed mixed fleet composition. Therefore, we now remove fleet sizing from the available decisions and instead constrain it to a constant fleet of 10 aircraft. We then test 11 predetermined fleet composition mixes ranging from 100% kerosene (E0K10) to 100% electric (E10K0).

1. Financial Performance and Stability

To understand the effect of fleet electrification on performance, Figure 15 presents the relative profit and financial stability (CV) for each period, benchmarked against the 100% kerosene fleet. The CV is used to normalize for the different profits and variances across time periods.
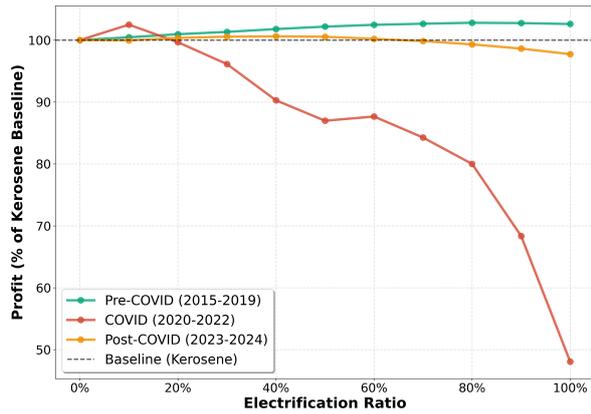
(a) Relative Profit
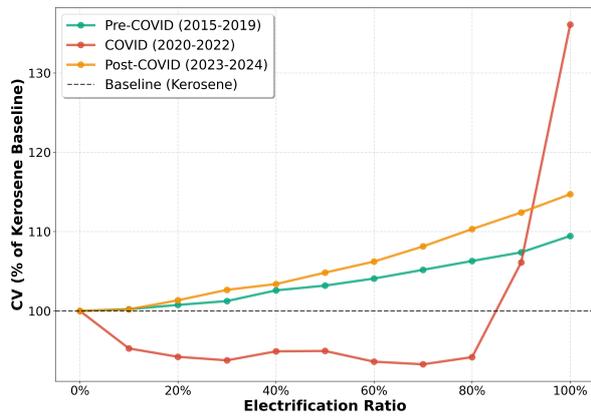
(b) Relative CV of profit

Figure 15. Relative Profit and Stability over Fleet Electrification. Line charts showing (a) Relative Profit and (b) CV across three time periods.
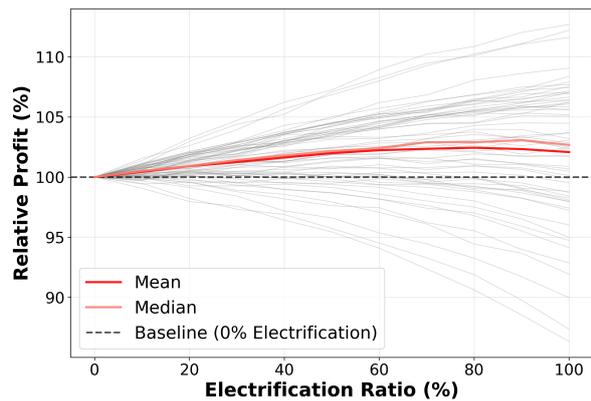
Figure 16. Pre-COVID Monthly Profit by Fleet Electrification. Plot showing profit by fleet composition for different months (2015–2019).

Several key findings emerge from this analysis:

- **Stable Periods (Pre- and Post-COVID):** Increasing electrification generally leads to modest profit gains in stable markets. Pre-COVID, an 80% electric fleet was optimal, increasing profits by 2–3% over a pure kerosene fleet (Figure 16). Post-COVID, a 40% mix performed best. Across both periods, a 100% electric fleet was the most volatile (highest CV), while a 100% kerosene fleet was the most stable (Figure 15b) While the mean profit generally increases with electrification, monthly performance varies, as shown in Figure 16.

- **Crisis Period (COVID):** The pandemic inverts these dynamics. Due to extremely high electricity prices severely limiting profitable routes, the fully electric fleet suffered the largest losses (approx. -50% relative profit). The most profitable strategy during COVID is a predominantly kerosene fleet (10% electric). Counterintuitively, introducing a small number of electric aircraft reduces volatility (as shown in Figure 15b), with the CV improving from 0% to 10% electrification, likely because the lower fixed costs of electric aircraft made them cheaper to ground than their kerosene counterparts.

2. Risk-Return Analysis

To formalize the trade-off between profitability and risk, we employ a framework adapted from Modern Portfolio Theory to plot the risk versus the return for each strategy [78]. Here, average monthly profit serves as the 'return' and the CV serves as the normalized 'risk'. Figure 17 plots the risk-return profile for each of the 11 fleet compositions. Each point represents a fleet mix, colored from red (0% electric) to green (100% electric). The star mark is explained further in section VI.C.3. Also note that although conventional portfolio theory uses standard deviation (SD), CV is acceptable and necessary in this case because the profits and volatilities differ significantly across time periods.

(a) 120 month (2015–2024)

(b) *Pre-COVID* (2015–2019)

(c) COVID (2020–2022)

(d) *Post-COVID* (2023–2024)
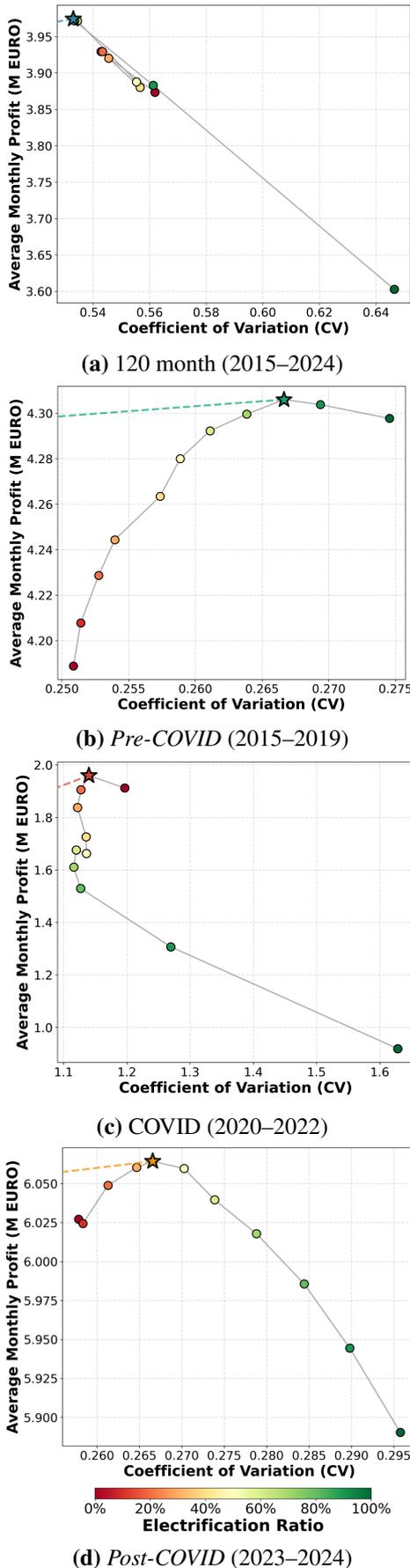
Figure 17. Risk-Return Profiles (Mean Profit vs. CV) for 11 fleet compositions across time periods.

The shape of the curve provides the most critical observation. All time periods exhibit a non-linear curve, indicating substantial interaction among the fleet types. A linear curve would indicate that performance is merely the simple weighted sum of individual fleet contributions, but the significant curvature shows that the fleets operate synergistically. Notably, the best profit strategy never equals the most stable strategy.

The curves are very dependent on the time period. The stable pre- and post-COVID markets exhibit standard risk-return curves where volatility increases with electrification and profit peaks at a mixed composition. The pure kerosene fleet anchors the low-risk end while the pure electric fleet represents the high-risk end. The COVID period, in contrast, shows a scattered vertical frontier where all strategies carried high risk for low returns. The full 120-month view appears erratic because it averages these distinct economic environments.

Also note the different axis scales for the three plots. The COVID period shows much lower profits, higher profit volatility, and a wider spread of both across fleet composition strategies as well.

3. Optimal Fleet Composition

We adopt another concept from Modern Portfolio Theory to calculate the optimal fleet composition from a risk-adjusted perspective. The Capital Allocation Line (CAL) is a line drawn from a hypothetical risk-free asset that is tangent to the curve. The point of tangency represents the portfolio (in this case, the fleet mix) that offers the highest return for each unit of risk (i.e., the highest Sharpe Ratio). In portfolio theory, the risk-free asset is the hypothetical asset that pays a risk-free rate, often modeled by short-term government treasury bills [78]. Applying this to airline fleet composition theory would require an equally fictitious zero-risk fleet composition. For this analysis, we assume a risk-free asset with zero volatility and the minimum mean profit for any fleet mix of that period. The CAL is the dashed line in Figure 17 with its tangency point marked by a star.

In this analysis, this strategy matches a max profit strategy, but with different fleet sizes, there could be small differences between the two strategies. These optimal strategies, along with other key performance metrics, are summarized in Table 11.

Table 11. Fleet Electrification Ratios Corresponding to Maximum Return, Minimum Risk, and Optimal Risk-Adjusted Performance (CAL) by Period (2015–2024)

Period	Good			Bad	
	Optimal (CAL)	Max Profit	Min Risk CV	Worst Profit	Max Risk CV
Pre-COVID	80%	80%	0%	0%	100%
COVID	10%	10%	70%	100%	100%
Post-COVID	40%	40%	0%	100%	100%
Full Period	70%	70%	70%	100%	100%

10% electrification implies 1 electric and 9 kerosene aircraft.

The analysis reveals that the optimal fleet strategy is highly dependent on the market environment:

- In the stable Pre-COVID market, a high electrification of 80% is optimal, maximizing profit with a manageable increase in risk
- During the volatile COVID crisis, the optimal strategy shifts dramatically to a predominantly kerosene fleet (10% electric) to minimize losses and navigate uncertainty
- In the Post-COVID recovery, a balanced hedge of 40% electric offers the best risk-adjusted returns
- Over the entire 120-month period, the average optimal strategy is a 70% electric fleet, a high figure driven by the fact that the profitable stable periods outweigh the shorter, though severe, crisis periods in the long-term average

Notably, homogeneous fleets are never optimal, with the pure electric strategy consistently marking the highest risk or worst profitability.

4. Network Structural Performance

Beyond the network's financial performance, the mixed fleet composition fundamentally alters the airline's network structure. To analyze this, we categorize routes by how they are served:

- **All-Electric / All-Kerosene:** Routes served exclusively by one aircraft type. We further split kerosene routes into whether they are outside of the range of an electric aircraft (range-infeasible)
- **Alternating Service:** Routes that switch between electric and kerosene aircraft across different months, showing how a mixed fleet can help keep routes in service optimally longer.
- **Simultaneous Service:** Routes flown by both

electric and kerosene aircraft in the same month

Figure 18 shows how the prevalence of these categories changes with the fleet's electrification ratio. As electrification increases, the network does not simply swap kerosene routes for electric ones. Instead, there is a significant increase in integrated strategies. The proportion of 'Alternating Service' and 'Simultaneous Service' routes rises with the electrification ratio. At 90% electrification, nearly 60% of routes are operated with some form of interaction between the two fleet types. This demonstrates that the two fleets work in concert, rather than in isolation. Furthermore, we see that only a small portion of the kerosene-only routes are out of reach for the electric aircraft, which concurs with our earlier finding in Figure 12 that a mixed-fleet strategy does not simply split routes between kerosene and electric aircraft by effective range.
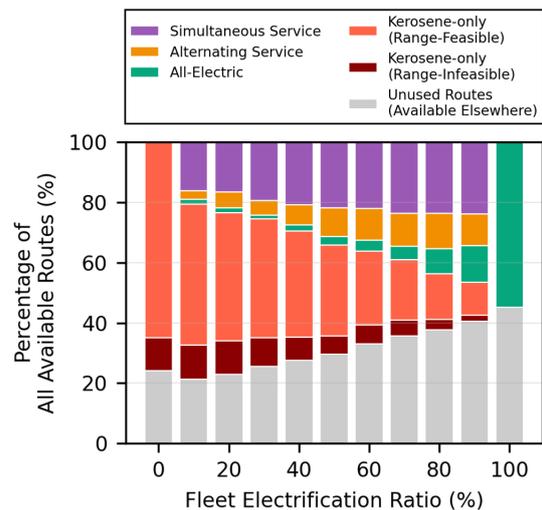
Figure 18. Route Service Categories by Fleet Composition (2015–2024). Chart showing the percentage of routes served by different operational strategies as the fleet electrification ratio increases.

Comparing low and high electrified fleets reveals a stark asymmetry in minority fleet utilization.

- With a **10% electric fleet (E1K9)**, the network remains overwhelmingly dominated by kerosene, with nearly 74% of routes being 'All-Kerosene'. The single electric aircraft is used opportunistically as a specialized, cost-saving tool rather than a network backbone. Practically no routes are dedicated solely to it (only 2.0% are 'All-Electric'). Instead, its primary role is collaborative: it is deployed on 71 'Simultaneous Service' routes (20.7%) to supplement capacity on prof-

itable kerosene-led routes, showing that the routes are ideal for both kerosene and electric aircraft. Electric aircraft also participate in a handful of 'Alternating Service' routes, showing that a portion of routes can switch between being ideal for kerosene and ideal for electric aircraft.

- With a **90% electric fleet (E9K1)**, the single kerosene aircraft demonstrates far greater strategic importance. It is solely responsible for 56 'All-Kerosene' routes (21.6%), ten times as many as the lone electric aircraft manages in the reverse scenario. Furthermore, it is deeply integrated into the network, participating in 46 'Alternating Service' routes and a remarkable 104 'Simultaneous Service' routes (40.2% of the total). This deep integration highlights a critical finding: even with a 90% electric fleet, only 20.5% of the network is 'All-Electric' operated. The kerosene aircraft is vital and is used throughout the network.

This asymmetry proves that a single kerosene aircraft provides widespread utility across the network. It integrates with a wide range of routes because it remains optimal across various scenarios. The analysis confirms that mixed fleets create synergistic value both financially and structurally. Alternating service routes further demonstrate how this flexibility extends network stability.

VII. Sensitivity, Verification, and Validation

To ensure robust results, we conduct a comprehensive sensitivity analysis in section VII.A, verify the internal model logic through systematic behavioral testing in section VII.B, and lastly perform validation against real-world data in section VII.C.

A. Sensitivity Analysis

This section presents a summary of the comprehensive sensitivity analysis on model parameters and results presented in full in Appendix G.

A quantitative assessment of individual parameters reveals that profitability is overwhelmingly driven by revenue factors (yield curve, load factor) and aircraft utilization (aircraft seats, flying hours per month). In contrast, the model shows lower sensitivity to technology-specific parameters, such as charging rates or marginal increases in aircraft range, suggesting that these are not the primary levers for profitability within the tested range.

Beyond marginal parameter changes, we also test the model's response to structural shifts. Testing with different hubs shows that Amsterdam Schiphol is the 2nd best airport in Europe to start EA operations from, but the results are relatively similar across the major EU hubs. We also find that computational performance is driven more by operational complexity than by scale, with mixed fleets and multi-stop routes significantly increasing runtime. Furthermore, the model's financial behavior is highly sensitive to the structure of its environment. While profit responds linearly to moderate changes in costs, we identify critical non-linear threshold effects. A switch to high-cost Sustainable Aviation Fuel (SAF), for example, causes a disproportionate drop in profit by rendering a large portion of the route network unviable. Most importantly, the fundamental structure of the network is dictated by the yield curve. The distance-based yield incentivizes a dense, short-haul network, whereas a flat yield shifts the optimal strategy toward longer-haul flights, which reduce the time spent on the ground and not earning money. While our results are sensitive to the selected yield curve, its use in previous literature gives us confidence in its validity. In all, the sensitivity analysis on our baseline parameterization gives us confidence in the robustness of our results.

B. Verification

This section presents a summary of the verification tests conducted, with the complete verification steps outlined in Appendix H.

To ensure the model's internal logic is sound, a systematic series of over 40 simple behavioral tests is conducted to verify that it responds predictably to changes in key parameters. These tests confirm that the model responds logically to variations in aircraft performance (e.g., range, speed), operational constraints (e.g., fleet size, turnaround times), and changes in energy prices. The outcomes of this extensive test suite confirm the model's logical consistency. This behavioral verification is complemented by robust software practices, including rigorous input checks for data integrity and alignment (e.g., ensuring non-negative battery capacity), comprehensive bounds checking, and systematic error handling. Together, these layers of verification, both against external data, internal logic, and within the code, provide confidence in the model's design.

C. Validation

Lastly, this section summarizes the validation tests conducted, which are detailed in Appendix I.

A comprehensive validation process is conducted on the model's core inputs and assumptions to ensure the credibility of its outputs. The passenger demand data aligns closely with separate Eurostat figures for the critical intra-EU market, and the network exhibits the necessary bidirectionality, justifying the UK demand extrapolation. Furthermore, the operating cost structures, particularly the share of kerosene costs, are consistent with established industry benchmarks, and the generated route networks are structurally comparable to real-world regional airline operations. A key finding from this process is that the model's revenue yield assumptions result in projected profit margins that are significantly higher than those of existing airlines. While partially offset by conservative electric aircraft cost estimates, this suggests the model's financial projections should be interpreted as optimistic, though excluding other cost factors could mitigate their impact.

VIII. Discussion

This research re-examines traditional strategic airline planning by adapting its methods for the unique context of electrified aviation. The shift from stable, spatially uniform kerosene costs to volatile, localized electricity prices, along with the new possibility for mixed fleet compositions, motivates this expansion. This discussion synthesizes our findings to build a new strategic playbook, identifying key characteristics of an optimal electrified network and offering directives for operators and researchers.

A. A Strategic Playbook for Electrified Aviation

The first step in this new playbook is acknowledging the value in including accurate electricity price information. Our findings demonstrate that future electrified aviation planning models cannot afford to use overly simplified electricity pricing data. We caution against using location-agnostic price assumptions, as they reduce profits by 0.8% in stable markets and can mask catastrophic losses of over 35% during volatile periods. For future airlines lacking perfect foresight, planners should prioritize predicting the *ranking* of airports by their electricity prices to unlock price arbitrage. Accurately forecast-

ing price *magnitude* is primarily significant for risk management during volatile periods, which punish overestimation more harshly than underestimation. Temporal granularity is the least performance-defining factor. In all, the non-uniformity of electricity prices presents a clear opportunity for network adaptation. This contrasts with the linear reaction forced by more uniform kerosene prices, revealing that electricity price volatility is not just a challenge to be mitigated, but a dynamic feature to be exploited for financial and structural advantage.

This price awareness enables an expansion of the strategic toolkit: elevating charging from an operational task to a strategic decision. While the operational problem of how much to refuel a kerosene aircraft is often tackled close to the departure date, our results show that pre-planning electric charging at the strategic level, likely months in advance, unlocks noticeable value. Sophisticated behaviors, such as "charge ferrying," emerge as a dominant strategy. Relying on simplified heuristics incurs a cost, reducing potential profits by approximately 1%, even though a 'charge-to-max' rule is a likely candidate for operational use due to the safety buffer it provides. Future planning models must therefore fully integrate charging decisions to remain competitive. This elevates "charge ferrying" to a modern equivalent of fuel tankering, but one optimized for cost arbitrage without the environmental penalties associated with carrying excess fossil fuel.

The second expansion of the strategic playbook involves leveraging the mixed fleet as a powerful instrument for both risk management and profit generation. Our risk-return analysis shows that specific mixed fleet compositions achieve superior risk-adjusted returns, an effect directly attributable to energy arbitrage between the decoupled electricity and kerosene markets. The resulting network optimization is also sophisticated. Rather than being split along simple range-based lines, electric and kerosene aircraft often share the same routes, either simultaneously or through alternating service, thereby maintaining route optimality for longer.

Beyond exploiting energy price differentials, the mixed fleet also shows unique structural choices. This is best illustrated by the asymmetric role of a minority kerosene aircraft in a fleet dominated by electric aircraft (9 out of 10). A single kerosene aircraft is assigned to a much larger set of routes than any single electric aircraft, serving 21% of

routes exclusively and participating in operations on nearly 80% of all routes. Conversely, in a kerosene-dominated fleet, a lone electric aircraft's operational scope is more focused, serving only 2% of routes exclusively. The model's extensive use of a single kerosene aircraft, with diminishing structural gains from a second kerosene aircraft, shows that a small kerosene share is sufficient to significantly boost network-wide performance. This finding, combined with the fact that a 100% homogeneous fleet is never optimal in a fixed-fleet analysis, underscores the structural necessity of diversification.

Looking ahead, the inherent uncertainty of electricity prices suggests that operational planning will need to be equally dynamic. Strategic models like ours provide a robust monthly plan, but future operational systems will need to account for forecast updates as the day of departure approaches, unlocking further gains through continuous replanning.

In all, this research reaffirms the potential of electrified aviation while mapping the significant strategic hurdles posed by electricity price dynamics. Success in this new era will not come from simply replacing one propulsion system with another, but from developing a new strategic playbook. This playbook must embrace flexibility, intelligently leverage information to mitigate risk, and use a diversified fleet to build a resilient and profitable airline for a sustainable future.

B. Assumptions and Limitations

The model's results should be interpreted in the context of several key assumptions and limitations, which are fully detailed in Appendix F. On a strategic level, the model operates in a simplified market by assuming passenger demand is fixed and inelastic, and by not accounting for competitive airline reactions. Operationally, it is constrained to a single-hub network architecture and presumes the widespread availability of unconstrained airport charging infrastructure, while also abstracting away factors like battery degradation. This distinction means the model is designed to determine what the optimal network and fleet strategy is, not how to execute it on a daily operational basis. Perhaps most significantly, the analysis relies on aggregated, country-level monthly electricity prices and continental kerosene prices, which inherently dampens the spatiotemporal volatility the model is designed

to exploit. The economic framework is further simplified by excluding power-based electricity charges. Furthermore, the findings are grounded in historical data, providing a validated baseline for current market conditions but explicitly not forecasting the future market dynamics into which this technology will be introduced. Lastly, the model's focus on analyzing the optimal strategy per month, instead of building a continuous operational strategy, could lead to different patterns emerging, however, the model still serves to benchmark how close each month's operationally feasible plan is to the optimum. Collectively, these factors position the study's findings as a strategic exploration under idealized conditions, rather than a precise operational forecast.

C. Recommendations for Future Work

This research establishes a strategic planning framework for electrified aviation. Recommendations focus on enhancing model fidelity, expanding operational scope, and integrating real-world constraints.

- **Replanning Framework:** Develop a multi-stage, rolling-horizon or stochastic planning model that updates the solution as forecasts improve in accuracy as the departure date approaches. By simulating decreasing uncertainty over time, this approach would quantify the financial value of operational flexibility and determine whether energy price volatility warrants the complexity of continuous replanning.
- **Service Reliability:** Implement a mixed-fleet assignment cost-minimization model with a *service-all-demand* constraint. This shifts the focus from pure profitability to service continuity, reflecting established airline priorities and quantifying the value of a mixed fleet in maintaining service on the same routes for longer.
- **Mixed-Fleet Planning:** This analysis establishes mixed-fleet planning as a compelling and largely unexplored research avenue. Further investigation is required to fully quantify how electric and kerosene assets can complement one another and to develop the sophisticated allocation strategies that capitalize on their respective strengths.
- **Airport Infrastructure Constraints:** Enhance the limits on total monthly energy availability or simultaneous charging capacity per airport. Incorporating these factors would reveal how infrastructure bottlenecks might become drivers of network design and profitability.

- **Battery Lifecycle:** Incorporate the financial impact of battery degradation by modeling efficiency loss based on usage cycles and fast charging. This introduces a crucial strategic trade-off between maximizing short-term aircraft utilization and preserving the long-term value of battery assets.
- **Regulatory Scenarios:** Extend the model by modifying cost and revenue parameters to reflect regulatory instruments: carbon taxes, subsidies, or SAF mandates.

IX. Conclusion

This research developed a strategic airline planning framework to address the risks and opportunities of volatile, spatiotemporal electricity prices. We address a critical gap in a literature dominated by simplified price assumptions, asking if these new market dynamics require an expanded strategic suite.

Our analysis yields three principal findings that form a new strategic playbook. First, a pure electric fleet, while profitable in stable markets, is financially fragile and vulnerable to energy price shocks. Second, we establish that spatiotemporal electricity prices directly impact strategic decisions. The value of this information is twofold: including prices is essential for survival in volatile markets, while ranking them is key for profit optimization. This reframes charging as a core strategic decision, elevating it from an operational task. Third, a mixed fleet emerges as the most robust solution, unlocking synergistic profits while preserving financial stability. Our fixed-fleet analysis confirms a 100% electric fleet is never optimal, underscoring the necessity of diversification.

In conclusion, this study provides a framework for quantifying the strategic value of integrating accurate electricity prices, charging decisions, and mixed-fleet dynamics into high-level airline planning. This work establishes strategic charging optimization and dynamic mixed-fleet assignment as compelling research avenues for building profitable, sustainable airline networks of the future.

References

[1] Justin, C. Y., Payan, A. P., and Mavris, D. N., "Integrated fleet assignment and scheduling for environmentally friendly electrified regional air mobility," *Transportation Research Part C: Emerging Technologies*, Vol. 138, 2022, p. 103567. doi:10.1016/j.trc.2022.103567, URL https://www.sciencedirect.com/science/article/pii/S0968090X22000158.

[2] Mistry, H., "Director Energy Transition," *Energy Transition*, 2022.

[3] Lee, D. S., Fahey, D. W., Skowron, A., Allen, M. R., Burkhardt, U., Chen, Q., Doherty, S. J., Freeman, S., Forster, P. M., Fuglestvedt, J., Gettelman, A., De León, R. R., Lim, L. L., Lund, M. T., Millar, R. J., Owen, B., Penner, J. E., Pitari, G., Prather, M. J., Sausen, R., and Wilcox, L. J., "The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018," *Atmospheric Environment*, Vol. 244, 2021, p. 117834. doi:10.1016/j.atmosenv.2020.117834, URL https://www.sciencedirect.com/science/article/pii/S1352231020305689.

[4] Air Transport Action Group, "Tracking aviation efficiency," , Jan. 2020.

[5] Tirtha, S. D., Bhowmik, T., and Eluru, N., "Understanding the factors affecting airport level demand (arrivals and departures) using a novel modeling approach," *Journal of Air Transport Management*, Vol. 106, 2023, p. 102320. doi:10.1016/j.jairtraman.2022.102320, URL https://www.sciencedirect.com/science/article/pii/S0969699722001399.

[6] "ACI World projects 22.3 billion passengers by 2053 | ACI World," , Feb. 2025. URL https://aci.aero/2025/02/26/aci-world-projects-22-3-billion-passengers-by-2053/.

[7] Connie van Uffelen, "Electric flight still a pipe dream," , Dec. 2018. URL https://www.tudelft.nl/en/delft-outlook/articles/electric-flight-still-a-pipe-dream.

[8] Bergero, C., Gosnell, G., Gielen, D., Kang, S., Bazilian, M., and Davis, S. J., "Pathways to net-zero emissions from aviation," *Nature Sustainability*, Vol. 6, No. 4, 2023, pp. 404–414. doi:10.1038/s41893-022-01046-9, URL https://www.nature.com/articles/s41893-022-01046-9.

[9] Schäfer, A. W., Barrett, S. R. H., Doyme, K., Dray, L. M., Gnadt, A. R., Self, R., O'Sullivan, A., Synodinos, A. P., and Torija, A. J., "Technological, economic and environmental prospects of all-electric aircraft," *Nature Energy*, Vol. 4, No. 2, 2019, pp. 160–166. doi:10.1038/s41560-018-0294-x, URL https://www.nature.com/articles/s41560-018-0294-x.

[10] Pettes-Duler, M., Roboam, X., and Sareni, B., "Integrated Optimal Design for Hybrid Electric Powertrain of Future Aircrafts," *Energies*, 2022. doi:10.3390/en15186719, URL https://consensus.app/papers/integrated-optimal-design-for-hybrid-electric-powertrain-pettes-duler-roboam/b566f865778f57d7b4a30586d3369a45/.

[11] Apanasevic, T., Li, J., and Forzati, M., "eFlight: Socio-economic analysis," *ISE Research Institutes of Sweden AB*, 2021.

[12] Qiao, G., Liu, G., Shi, Z., Wang, Y., Ma, S., and Lim, T. C., "A review of electromechanical actuators for More/All Electric aircraft systems," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, Vol. 232, No. 22, 2018, pp. 4128–4151. doi:10.1177/0954406217749869, URL https://journals.sagepub.com/doi/10.1177/0954406217749869.

[13] Susan X. Ying, *Electric Aircraft*, Vol. 5, 2023.

[14] Kinene, A., and Birolini, S., "Optimization of subsidized air transport networks using electric aircraft," *Transportation Research Part B: Methodological*, Vol. 190, 2024, p. 103065. doi:10.1016/j.trb.2024.103065, URL https://linkinghub.elsevier.com/retrieve/pii/S0191261524001899.

[15] "Aviation Fuels - an overview | ScienceDirect Topics," , 2021. URL https://www-sciencedirect-com.tudelft.idm.oclc.org/topics/engineering/aviation-fuels.

[16] Naumann, M., and Suhl, L., "How does fuel price uncertainty affect strategic airline planning?" *Operational Research*, Vol. 13, No. 3, 2013, pp. 343–362. doi:10.1007/s12351-012-0131-0, URL https://link.springer.com/article/10.1007/s12351-012-0131-0.

[17] McCausland, R., and IATA, "ReFuelEU Aviation Handbook," *ReFuelEU Aviation Handbook*, 2024.

[18] Seet, C., "The Ins & Outs Of The Fuel Tankering Debate," , May 2023. URL https://simpleflying.com/fuel-tankering-debate-guide/, section: Guides.

[19] IATA, "Fact Sheet Fuel," , 2024.

[20] "Chat of the Week: A renewed rise in the jet crack spread adds to cost preasure," , Oct. 2023. URL https://www.iata.org/en/iata-repository/publications/economic-reports/a-renewed-rise-in-the-jet-crack-spread-adds-to-cost-pressure/.

[21] opisteam, "Jet Fuel Pricing 101," , Jul. 2023. URL https://www.opisnet.com/blog/jetfuel/.

[22] FuelsEurope, "Statistics," , Nov. 2024. URL https://www.fuelseurope.eu/statistics.

[23] "Jet Fuel Price Monitor," , May 2025. URL https://www.iata.org/en/publications/economics/fuel-monitor/.

[24] of European Union, C., "How is EU electricity produced and sold?" , Jan. 2025. URL https://www.consilium.europa.eu/en/infographics/how-is-eu-electricity-produced-and-sold/.

[25] "Live 24/7 CO_2 emissions of electricity consumption," , Jun. 2025. URL https://app.electricitymaps.com/map/72h/hourly.

[26] Van Der Wiel, K., Bloomfield, H. C., Lee, R. W., Stoop, L. P., Blackport, R., Screen, J. A., and Selten, F. M., "The influence of weather regimes on European renewable energy production and demand," *Environmental Research Letters*, Vol. 14, No. 9, 2019, p. 094010. doi:10.1088/1748-9326/ab38d3, URL https://iopscience.iop.org/article/10.1088/1748-9326/ab38d3.

[27] Gonçalves, A. C. R., Costoya, X., Nieto, R., and Liberato, M. L. R., "Extreme weather events on energy systems: a comprehensive review on impacts, mitigation, and adaptation measures," *Sustainable Energy Research*, Vol. 11, No. 1, 2024, p. 4. doi:10.1186/s40807-023-00097-6, URL https://doi.org/10.1186/s40807-023-00097-6.

[28] Rantaniemi, J., Jääskeläinen, J., Lassila, J., and Honkapuro, S., "A Study on the Impact of Distance-Based Value Loss on Transmission Network Power Flow Using Synthetic Networks," *Energies*, Vol. 15, No. 2, 2022, p. 423. doi:10.3390/en15020423, URL https://www.mdpi.com/1996-1073/15/2/423.

[29] Pregger, T., Lavagno, E., Labriet, M., Seljom, P., Biberacher, M., Blesl, M., Trieb, F., O'Sullivan, M., Gerboni, R., Schranz, L., Cabal, H., Lechón, Y., and Zocher, D., "Resources, capacities and corridors for energy imports to Europe," *International Journal of Energy Sector Management*, Vol. 5, No. 1, 2011, pp. 125–156. doi:10.1108/17506221111120938, URL https://doi.org/10.1108/17506221111120938, publisher: Emerald Group Publishing Limited.

[30] International Energy Agency Energy Technology Systems Analysis Programme, "Electricity Transmission and Distribution," , Apr. 2014.

[31] Hemmings, B., "Taxing aviation fuel in the EU," , Jun. 2019.

[32] Commission, E., "Excise Duties: Other Energy Tax Legislation - European Commission," , 2025. URL https://taxation-customs.ec.europa.eu/excise-duties-other-energy-tax-legislation_en.

[33] Oesingmann, K., "The impact of economic agreements and environmental instruments on air transport demand:," *MSc. Thesis*, 2022.

[34] Thießen, F., "Taxes and Fees," *Air Transport and its Subsidies*, edited by F. Thießen, Springer Fachmedien, Wiesbaden, 2022, pp. 7–21. URL https://doi.org/10.1007/978-3-658-38899-7_2.

[35] Pache, E., "Implementation of Kerosene Fuel Taxation in Europe Part I: Legal Foundations and Issues," , Jun. 2019.

[36] A4E, "A4e's position on the energy taxation directive," , Apr. 2023.

[37] Holmberg, A., "Comparative Cost Analysis of Plug-In Charging and Battery Swapping Systems for Electric Aircraft," Ph.D. Thesis, KTH Royal Institute of Technology, Aug. 2024.

[38] van Santen, T., "Interview with ROCC employee," , Mar. 2025.

[39] Brown, G., "Making Sense of Demand Charges: What Are They and How Do They Work?" , Jun. 2017. URL https://www.renewableenergyworld.com/solar/utility-scale/making-sense-of-demand-charges-what-are-they-and-how-do-they-work/.

[40] Etschmaier, M. M., and Mathaisel, D. F. X., "Airline Scheduling: An Overview," *Transportation Science*, Vol. 19, No. 2, 1985, pp. 127–138. doi:10.1287/trsc.19.2.127, URL https://pubsonline.informs.org/doi/10.1287/trsc.19.2.127.

[41] Zeighami, V., and Soumis, F., "Combining Benders' Decomposition and Column Generation for Integrated Crew Pairing and Personalized Crew Assignment Problems," *Transportation Science*, Vol. 53, No. 5, 2019, pp. 1479–1499. doi:10.1287/trsc.2019.0892, URL https://pubsonline.informs.org/doi/10.1287/trsc.2019.0892.

[42] Shao, S., Sherali, H. D., and Haouari, M., "A Novel Model and Decomposition Approach for the Integrated Airline Fleet Assignment, Aircraft Routing, and Crew Pairing Problem," *Transportation Science*, Vol. 51, No. 1, 2017, pp. 233–249. doi:10.1287/trsc.2015.0623, URL https://pubsonline.informs.org/doi/10.1287/trsc.2015.0623.

[43] Eltoukhy, A. E., Chan, F. T., and Chung, S. H., "Airline schedule planning: a review and future directions," *Industrial Management & Data Systems*, Vol. 117, No. 6, 2017, pp. 1201–1243. doi:10.1108/IMDS-09-2016-0358, URL https://www.proquest.com/docview/1915806409/abstract/F164B36FAD774027PQ/1.

[44] Kınay, O. B., Gzara, F., and Alumur, S. A., "Full cover charging station location problem with routing," *Transportation Research Part B: Methodological*, Vol. 144, 2021, pp. 1–22. doi:10.1016/j.trb.2020.12.001, URL https://www.sciencedirect.com/science/article/pii/S0191261520304434.

[45] Van Oosterom, S., and Mitici, M., "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*, Vol. 155, 2023, p. 104313. doi:10.1016/j.trc.2023.104313, URL https://linkinghub.elsevier.com/retrieve/pii/S0968090X23003029.

[46] Lindberg, M., and Leijon, J., "Effects on Airport Operations from a New Regional Electric Flight Network in Northern Scandinavia," *2024 IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC)*, 2024, pp. 1–6. doi:10.1109/ESARS-ITEC60450.2024.10819765, URL https://ieeexplore.ieee.org/document/10819765/?arnumber=10819765.

[47] Salucci, F., Trainelli, L., Faranda, R., and Longo, M., "An optimization Model for Airport Infrastructures in Support to Electric Aircraft," *2019 IEEE Milan PowerTech*, 2019, pp. 1–5. doi:10.1109/PTC.2019.8810713, URL https://ieeexplore.ieee.org/abstract/document/8810713.

[48] Trainelli, L., Riboldi, C. E., Rolando, A., and Salucci, F., "Methodologies for the initial design studies of an innovative community-friendly miniliner," *IOP Conference Series: Materials Science and Engineering*, Vol. 1024, No. 1, 2021, p. 012109. doi:10.1088/1757-899X/1024/1/012109, URL https://iopscience.iop.org/article/10.1088/1757-899X/1024/1/012109.

[49] Kinene, A., Birolini, S., Cattaneo, M., and Granberg, T. A., "Electric aircraft charging network design for regional routes: A novel mathematical formulation and kernel search heuristic," *European Journal of Operational Research*, Vol. 309, No. 3, 2023, pp. 1300–1315. doi:10.1016/j.ejor.2023.02.006, URL https://www.sciencedirect.com/science/article/pii/S037722172300125X.

[50] Sahoo, S., Zhao, X., and Kyprianidis, K., "A Review of Concepts, Benefits, and Challenges for Future Electrical Propulsion-Based Aircraft," *Aerospace*, 2020. doi:10.3390/aerospace7040044, URL https://consensus.app/papers/a-review-of-concepts-benefits-and-challenges-for-future-sahoo-zhao/4736dc715e355a34a191778b7e9d811a/.

[51] Kinene, A., Granberg, T. A., Birolini, S., Adler, N., Polishchuk, V., and Skoglund, J.-M., "An auction framework for assessing the tendering of subsidised routes in air transportation," *Transportation Research Part A: Policy and Practice*, Vol. 159, 2022, pp. 320–337. doi:10.1016/j.tra.2022.03.002, URL https://www.sciencedirect.com/science/article/pii/S0965856422000490.

[52] Pereira, M., "Short-range route scheduling for electric aircraft with battery-charging and battery-swapping constraints," Ph.D. Thesis, Delft University of Technology, Nov. 2019.

[53] van Amstel, "Optimizing the Energy and Charging Infrastructure Costs for Regional Electric Aircraft Operations," Ph.D. Thesis, Delft University of Technology, Mar. 2023.

[54] Hou, B., Bose, S., Marla, L., and Haran, K., "Impact of Aviation Electrification on Airports: Flight Scheduling and Charging," *IEEE Transactions on Intelligent Transportation Systems*, Vol. 25, No. 3, 2024, pp. 2342–2354. doi:10.1109/TITS.2023.3324310, URL https://ieeexplore.ieee.org/document/10296862/.

[55] Westin, J., Olsson, L., and Åhag, P., "Network Design Optimization for Regional Electric Aviation in Northern Scandinavia," *2024 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 2024, pp. 400–404. doi:10.1109/IEEM62345.2024.10856984, URL https://ieeexplore.ieee.org/abstract/document/10856984.

[56] Vehlhaber, F., and Salazar, M., "Airport infrastructure sizing for a regional electric aviation network," 2024.

[57] Vehlhaber, F., and Salazar, M., "Electric Aircraft Assignment, Routing, and Charge Scheduling Considering the Availability of Renewable Energy," *IEEE Control Systems Letters*, Vol. 7, 2023, pp. 3669–3674. doi:10.1109/LCSYS.2023.3339998, URL https://ieeexplore.ieee.org/abstract/document/10345712.

[58] Vehlhaber, F., and Salazar, M., "A Model Predictive Control Scheme for Flight Scheduling and Energy Management of Electric Aviation Networks," , Apr. 2024. doi:10.48550/arXiv.2404.09282, URL http://arxiv.org/abs/2404.09282.

[59] Kinene, A., "Interview with Alan Kinene," , May 2025.

[60] Birolini, S., "Interview Birolini," , Jul. 2025.

[61] Aerosapce, E., "Elysian Aircraft," , 2025. URL https://www.elysianaircraft.com.

[62] "KLM SafetyHerald," , 2025. URL https://www.klmsafetyherald.com/klmc-e175-e190-fleet.

[63] Chan, B., Deng, Y., Tran, N., Wu, H., Ikeda, M., Cinar, G., and Li, M. Z., "Optimizing fleet assignment decisions for regional airlines with hybrid electric aircraft uptake," 2024.

[64] Kruidenier, W. L., "Integrated Flight Scheduling and Routing of Hybrid and Electric Aircraft: Enhancing Network Performance through Partial Recharging," 2025.

[65] Exalto, J., "Elysian Interview," , Jun. 2025.

[66] "Sustainability in the end-of-life phase of aircraft - What happens after airplanes fly their last trip | EASA," , 2023. URL https://www.easa.europa.eu/en/light/topics/sustainability-end-life-phase-aircraft.

[67] Eurocontrol, "26 Fleet age – EUROCONTROL Standard Inputs for Economic Analyses," , 2022. URL https://ansperformance.eu/economics/cba/standard-inputs/latest/chapters/fleet_age.html, release 10.0.1.

[68] Eurocontrol, "18 Turnaround time – EUROCONTROL Standard Inputs for Economic Analyses," , 2022. URL https://ansperformance.eu/economics/cba/standard-inputs/latest/chapters/turnaround_time.html, release 10.0.1.

[69] Kafle, S., "Short & Sharp: How Does Ryanair Achieve Its 25-Minute Aircraft Turnarounds?" , Jun. 2024. URL https://simpleflying.com/ryanair-aircraft-turnaround-guide/, section: Airlines.

[70] Eurostat, "Eurostat Database," , 2025. URL https://ec.europa.eu/eurostat/data/database.

[71] "Harmonized Index of Consumer Prices: Passenger Transport by Air for Euro Area (19 Countries)," , Jun. 2025. URL https://fred.stlouisfed.org/series/CP0733EZ19M086NEST.

[72] OurAirports, "Open data @ OurAirports," , 2025. URL https://ourairports.com/data/.

[73] Dobruszkes, F., and Peeters, D., "The magnitude of detours faced by commercial flights: A global assessment," *Journal of Transport Geography*, Vol. 79, 2019, p. 102465. doi:10.1016/j.jtrangeo.2019.102465, URL https://www.sciencedirect.com/science/article/pii/S0966692318305544.

[74] Ember, "European Wholesale Electricity Price Data," , 2025. URL https://ember-energy.org/data/european-wholesale-electricity-price-data.

[75] Eurostat, "Electricity prices for non-household consumers bi-annual data (from 2007 onwards)," , Apr. 2025. doi:10.2908/NRG_PC_205, URL https://ec.europa.eu/eurostat/databrowser/product/page/NRG_PC_205.

[76] EIA, "U.S. Energy Information Administration - EIA - Independent Statistics and Analysis," , Mar. 2025. URL https://www.eia.gov/electricity/wholesale/.

[77] Chereau, D., "Kerosene fuel price markup," , Jun. 2025. Email contact with IATA Head of Fuel Energy Transiation.

[78] "Modern portfolio theory," , Sep. 2025. URL https://en.wikipedia.org/w/index.php?title=Modern_portfolio_theory&oldid=1308968419, page Version ID: 1308968419.

[79] Nowakowski, A., "The Complex Art of Aircraft Utilization," , Dec. 2023. URL https://airwaysmag.com/legacy-posts/art-of-aircraft-utilization.

[80] Lufthansa Group, "Airbus A320," , 2025. URL https://www.lufthansagroup.com/en/company/fleet/brussels-airlines/airbus-a320.html.

[81] KLM, "Stoelindeling en details van KLM's Boeing 737-800," , 2025. URL https://www.klm.nl/information/travel-class-extra-options/aircraft-types/boeing-737-800.

[82] Eurocontrol, "12 Aircraft operating costs – EUROCONTROL Standard Inputs for Economic Analyses," , 2022. URL https://ansperformance.eu/economics/cba/standard-inputs/latest/chapters/aircraft_operating_costs.html, release 10.0.1.

[83] De Vries, R., Wolleswinkel, R. E., Hoogreef, M., and Vos, R., "A New Perspective on Battery-Electric Aviation, Part II: Conceptual Design of a 90-Seater," *AIAA SCITECH 2024 Forum*, American Institute of Aeronautics and Astronautics, Orlando, FL, 2024. doi:10.2514/6.2024-1490, URL https://arc.aiaa.org/doi/10.2514/6.2024-1490.

[84] Maaz, A., and Memon, D. O., "How Do Pilots Decide When To Begin Their Descent?" , Oct. 2022. URL https://simpleflying.com/how-do-pilots-decide-when-to-begin-their-descent/, section: Guides.

[85] Eurocontrol, "38 Taxi time – EUROCONTROL Standard Inputs for Economic Analyses," , 2022. URL https://ansperformance.eu/economics/cba/standard-inputs/latest/chapters/taxiing_times.html, release 10.0.1.

[86] Orpano, S., "How Much Does A Boeing 737 Cost?" , Mar. 2024. URL https://simpleflying.com/how-much-does-a-boeing-737-cost/, section: Aircraft.

[87] van Enter, E. J., "Energy consumption of baggage handling systems," 2018. URL https://repository.tudelft.nl/record/uuid:1501d592-3a86-4e8c-bb8d-c3c1772d2378.

[88] Misra, A., "Summary of 2017 NASA Workshop on Assessment of Advanced Battery Technologies for Aerospace Applications," , Jan. 2018. URL https://ntrs.nasa.gov/citations/20180001539.

[89] Song, M.-K., Zhang, Y., and Cairns, E. J., "A Long-Life, High-Rate Lithium/Sulfur Cell: A Multi-faceted Approach to Enhancing Cell Performance," *Nano Letters*, Vol. 13, No. 12, 2013, pp. 5891–5899. doi:10.1021/nl402793z, URL https://doi.org/10.1021/nl402793z.

[90] Justin, C. Y., Payan, A. P., Briceno, S. I., German, B. J., and Mavris, D. N., "Power optimized battery swap and recharge strategies for electric aircraft operations," *Transportation Research Part C: Emerging Technologies*, Vol. 115, 2020, p. 102605. doi:10.1016/j.trc.2020.02.027, URL https://www.sciencedirect.com/science/article/pii/S0968090X19310241.

[91] Commission, E., "About the EU ETS - European Commission," , 2025. URL https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/about-eu-ets_en.

[92] Hartley, P., "The 10 Most Popular Airline Routes In The US," , Oct. 2025. URL https://simpleflying.com/10-most-popular-airline-routes-in-the-us/, section: Airlines.

[93] IATA, "Factsheet fuel," , 2025.

[94] "Air passenger transport statistics - Statistics Explained - Eurostat," , Nov. 2024. URL https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Air_passenger_transport_statistics.

[95] "66.8 million in 2024 – number of travellers at Schiphol continues to increase," , Jan. 2025. URL https://news.schiphol.com/66-million-in-2024-number-of-travellers-at-schiphol-continues-to-increase/.

[96] "Top airlines by operating margin," , 2025. URL https://companiesmarketcap.com/airlines/airlines-ranked-by-operating-margin/.

[97] Luthansa Group, "Annual report 2024," , Apr. 2025. URL https://report.lufthansagroup.com/2024/annual-report/en/.

[98] IAG, "Annual reports," , 2024. URL https://www.iairgroup.com/investors-and-shareholders/financial-reporting/annual-reports/.

[99] Airfrance KLM Group, "Full Year 2024 results | AIR FRANCE KLM," , 2024. URL https://www.airfranceklm.com/en/newsroom/full-year-2024-results.

[100] Ryanair Group, "Annual Report Ryanair 2024," , 2024. URL https://investor.ryanair.com/wp-content/uploads/2024/06/Ryanair-2024-Annual-Report.pdf.

[101] Easyjet PLC, "easyJet plc - 2024 Annual Report," , Dec. 2024. URL https://corporate.easyjet.com/investors/reports-and-presentations/presentations/presentation-details/2024/2024-Annual-Report/default.aspx.

[102] Finnair, "Finnair Oyj - Reports and presentations," , Jun. 2025. URL https://investors.finnair.com/en/reports_and_presentations.

[103] IATA, "Unveiling the biggest airline costs," , Jun. 2024. URL https://www.iata.org/en/publications/newsletters/iata-knowledge-hub/unveiling-the-biggest-airline-costs/.

Statement on AI Use: For coding, models such as Claude Code (using Claude's Opus 4.5 or Sonnet 4.5 models) or Cursor (using Composer-1) were used. For writing, Gemini 2.5 and 3.0 Pro, along with Grok 4.1 and Grammarly, were used.

Part I

Appendix

A. Input Data

This appendix provides detailed additional information on the data, parameters, and assumptions used in this research. It includes descriptions of the model architecture, key inputs and hyperparameters, yield estimation methodologies, aircraft specifications, passenger demand patterns, and analyses of energy price volatility across Europe.

Model Architecture
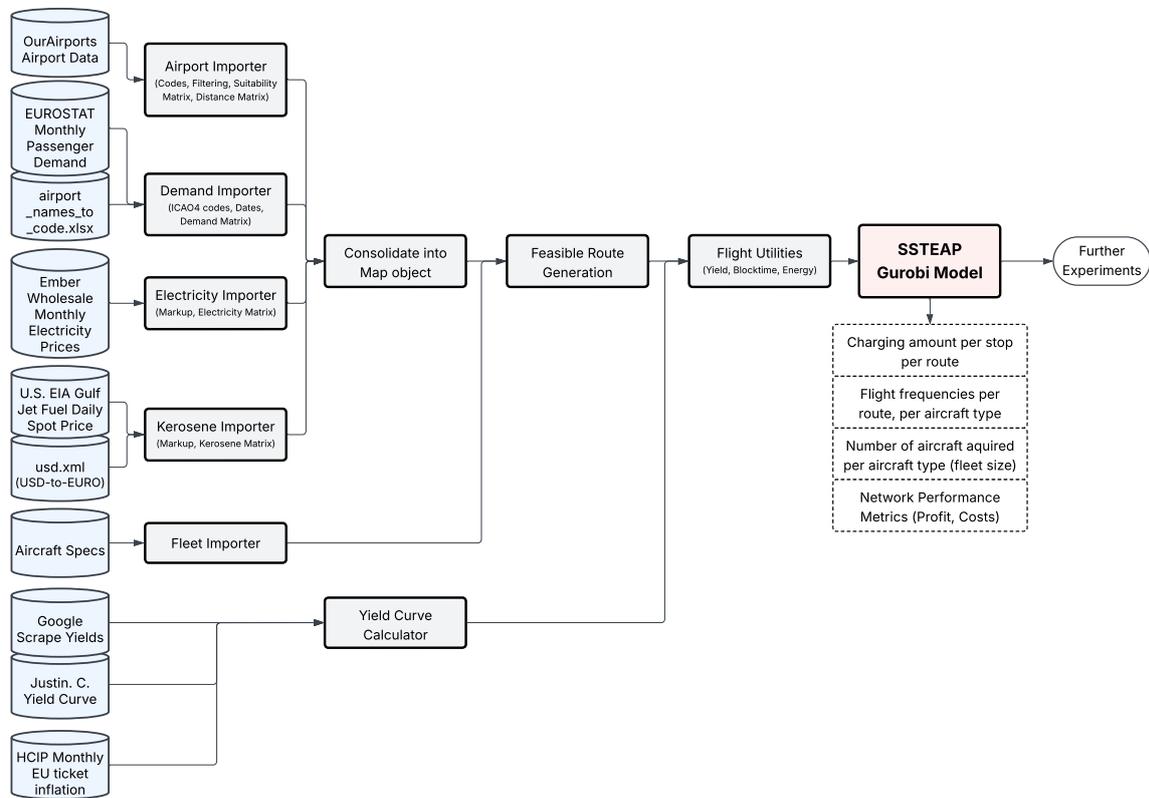
Figure 19. SSTEAP Model Architecture. Flowchart illustrating data inputs, processing steps, and integration with the Gurobi optimization model.

Model Inputs

Table 12. Detailed description and justification of model parameters, hyperparameters, and operational assumptions.

Parameter	Value	Value Justification
Model Hyperparameters		
Gurobi solver's optimality gap	0.1%	Testing indicates that optimal solutions are consistently reached at a 0.1% gap.
Route Generation		
Max. intermediate stops per route	2	Set to 2 as a computational constraint. Runtime increased to hours with 3 stops compared to 5 seconds for 2 stops.
Min. distance per flight leg	150 km	Other transportation methods provide better utility under 150 km, while this minimum still allows for the popular BXL–AMS flight.
Airports		
Airport type	large	1) Historical demand data is concentrated toward large airports. Simulating EA operations using only demand to smaller airports would underestimate potential demand. 2) Large airports are likeliest to have EA infrastructure built first.
Hub airport	EHAM	The research uses the Elysian E9X aircraft. Elysian is a Dutch electric aviation company based at Schiphol.
Fleet and Operations		
Max. fleet size	10	Initial EA fleets can be expected to start small.
Max. load factor per leg	78.6%	The mean load factor in EU27 between 2015–2024 is 78.60%. Using a fixed maximum loadfactor for the entire network was also applied in [1]
Route lengthening	107%	The mean route lengthening of flight paths compared to their great-circle distance [73].
Max. monthly operating hours per aircraft (incl. charging)	315 h	Derived from mean LCC daily utilization (9.1 h) [79], plus a buffer for charging and TAT (1.27 h), yielding 10.37 h/day, then multiplied by 30.4 average days per month to reach 315 h. Future research could consider higher maximum operating hours for electric aircraft compared to kerosene aircraft to account for the 'free' charging that can happen overnight.
Financial Inputs		
Min. profit margin per route	10%	Set higher than the 2024 mean EU airline margin (5.6%) to account for unmodeled costs (e.g., overhead) and the novelty of electric aviation.
Max. demand market share per leg	10%	Represents a 10% maximum cap on market share, reflecting a typical share for major European airlines.
Yield curve scaler	0.4	Explained below.
Electricity price markup	140%	Represents the estimated price increase from wholesale spot prices to industrial end-user prices in the EU. Estimate retrieved via e-mail contact with the IATA head of Fuel Energy Transition [77].
Kerosene price markup	110%	Based on correspondence with an IATA representative to estimate the "at-the-wing" price [77].

Yield Curve Selection

Route-level yields (€/pax-km) are estimated by adapting the distance-based curve methodology from Justin et al. [1], as granular European fare data is not publicly available. The curve is adjusted for inflation and calibrated against a sample of 206 routes from Google Flights in Europe. A final linear scaling factor of 0.4 was applied to align the curve with the European market context, balancing empirical data with the need to account for auxiliary revenues. The resulting yield curve is shown in Figure 20. Furthermore, seasonal yield trends are modeled by scaling the curve using the monthly Harmonized Index of Consumer Prices (HCIP) for airfares in Europe [71].
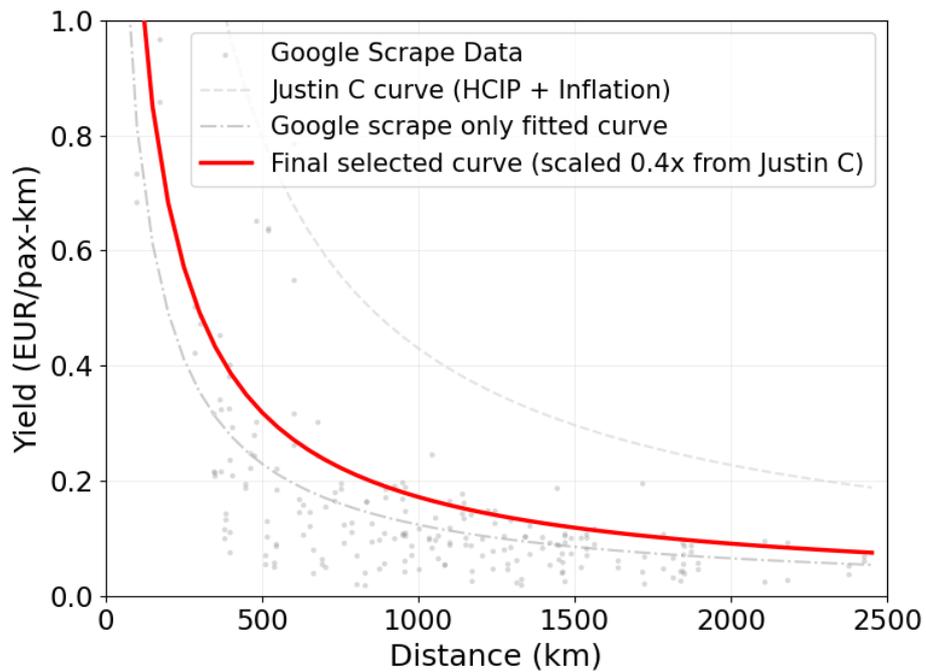
Figure 20. Distance-to-Yield Curve Calibration. Scatter plot showing yield per passenger-kilometer against flight distance. Comparing observed Google Flights data (grey dots) with the yield curve from Justin et al. [1], resulting in the adapted curve (red) used in this research.

Aircraft Specifications

Table 13. Comparison of Aircraft Parameters.

Parameter	1	2	3	4	Unit	Sources
Name	E9X-440	ERJ-175	A320	B737		
Type	Electric	Kerosene	Kero.	Kero.		
Operational						
Passenger Capacity	90	78	180	186	pax	[64, 80, 81]
Design Range	1000	3,334	3,900	4,200	km	[64, 80, 81]
Cruise Speed	648	850	840	850	km/h	[64, 82]
Cruise Altitude	7.5	11	11	11	km	E9X [65]; Typ. [82]
Climb Gradient	8	6*	6*	6*	%	E9X [83]; Others Est.
Descent Angle	3	3	3	3	°	Typical [84]
Ascend/Descend Velocity	352	463*	454*	459*	km/h	Ratio applied to Cruise Velocity
Emergency						
Diversion Range	150	185	200*	200*	km	[83]
Loiter Time	30	45	45	45	min	[83]
Turn Around Time						
Minimum TAT	30	30	35	35	min	LCC Target [68, 69]
Charge Setup	15	–	–	–	min	E9X [65]
Taxi Time	21	21	21	21	min	EU Mean [85]
Energy Storage						
Battery Capacity	15	–	–	–	MW h	[64]
Charging Rate	20	–	–	–	MW	[64]
SoC Range	10–95	–	–	–	%	[65]
Energy Efficiency	0.167	–	–	–	kWh/(pax · km)	Calculated
Fuel Capacity	–	11,625	27,200	26,025	L	[64, 80, 81]
Fuel Efficiency	–	0.038	0.031	0.027	kg/(pax · km)	Calculated (Linear)
Costs						
New Price	34.8	50*	122.4	95.5	M €	[64, 86]
Lifespan	25*	25*	25*	25*	years	Estimated [67]
Fixed Costs	116	167	408	318	k€/ month	Calculated (25yr)
Operating Cost	0.095*	0.069	0.034	0.036	€/(pax · km)	[82]

* = Value is estimated based on sources or derived from other stated values

Demand Data

Figure 21 shows the demand matrix for June 2024, illustrating the density of monthly passenger demand in the EU and the number of choices the model must select from. Note that even though our model operates from Amsterdam Schiphol Airport, because we allow for multi-leg routes, demand between other airports is also considered.

Figure 22 presents a histogram of passenger demand distributed across various flight distances for June 2024, highlighting key statistics such as total passengers, weighted average, and median distance.

Figure 23 depicts the evolution of total monthly passenger demand from 2015 to 2025, revealing seasonal fluctuations and overall trends.

(a) Standard view   **(b)** Zoomed in
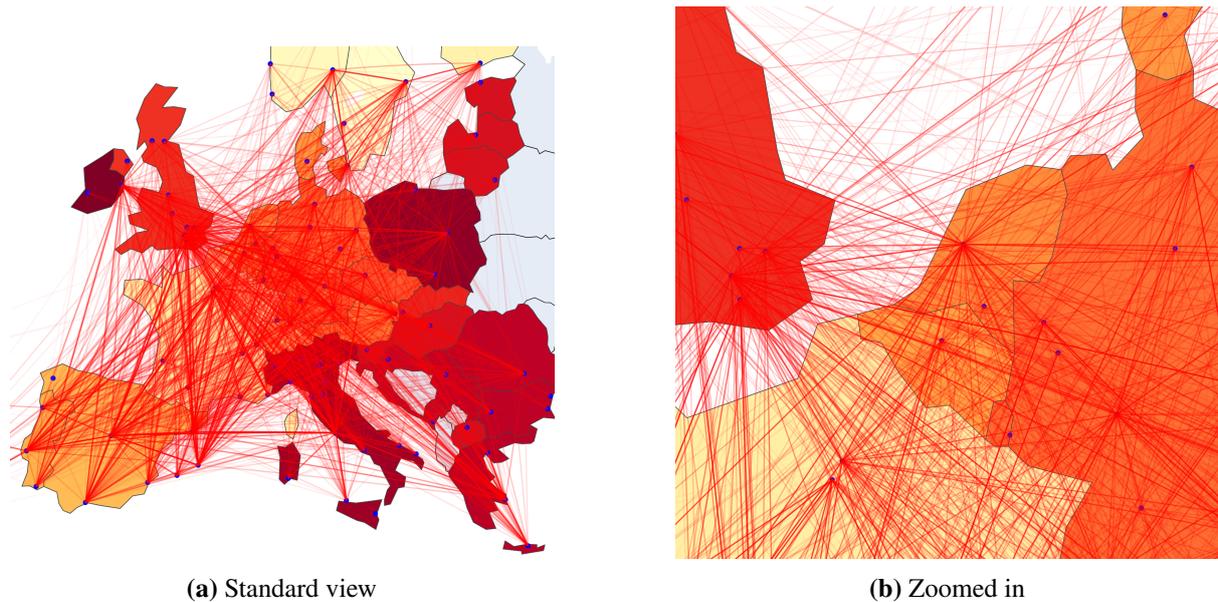
Figure 21. EU Demand Matrix (June 2024). Maps visualizing the density of passenger demand flows across Europe in (a) standard view and (b) zoomed-in view.
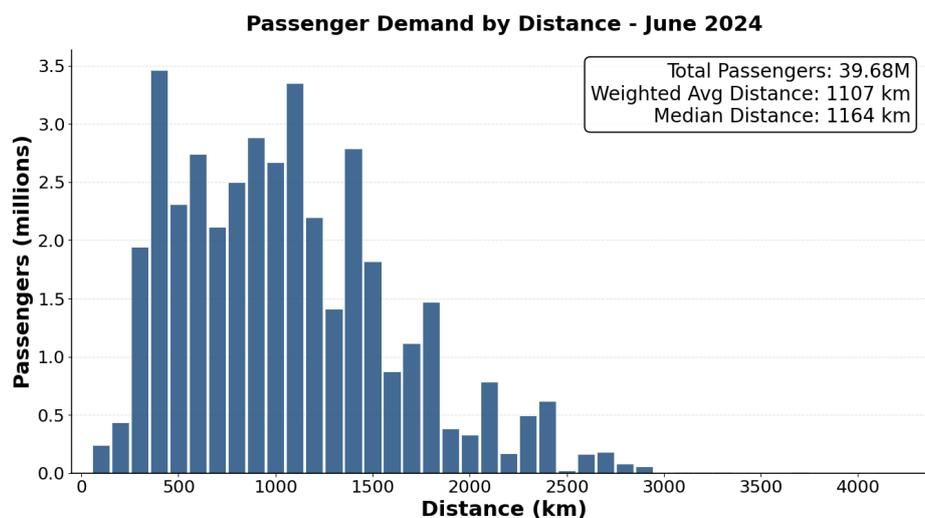
Figure 22. Demand by Leg Distance (June 2024). Histogram displaying the distribution of total passenger demand across different flight distances.
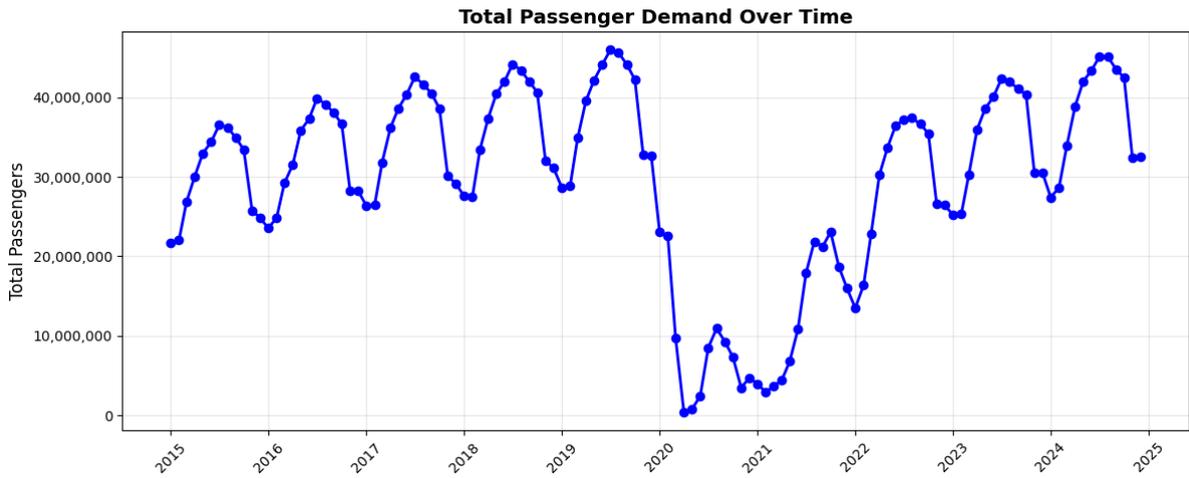
Figure 23. Total Passenger Demand Over Time. Line chart tracking total monthly passenger demand input into the model from 2015 through 2025.

Energy Data Analysis

While Section III.B analyzes Dutch energy prices to highlight volatility faced by a hub operator, this section extends the comparison to EU-wide averages. This broader scope confirms that the observed volatility in electricity prices is not a Netherlands-specific phenomenon. Averaging across countries can mask local extremes, yet even at the aggregate level, electricity exhibits significantly higher variability than kerosene, reinforcing the need for adaptive planning strategies.

(a) Frequency of large MoM changes

(b) Spread of MoM changes
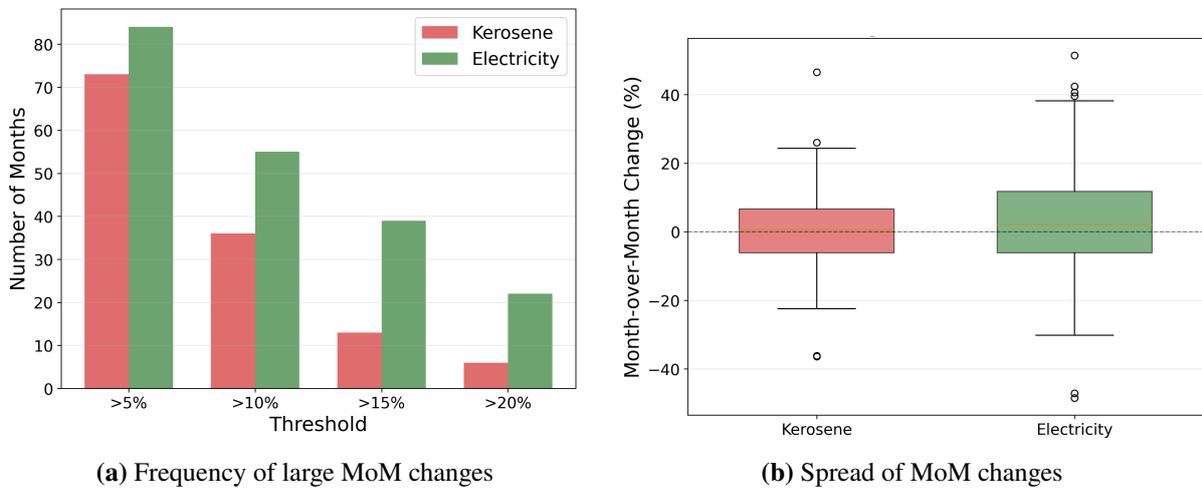
Figure 24. EU-Wide Energy Price Volatility (2015–2024). Bar charts comparing the (a) frequency and (b) spread of month-over-month price changes for kerosene versus electricity.

B. General Supplementary Results

Table 14. Total energy charged and share of total network charging for top 10 airports for a 10-aircraft E9X fleet in June 2024.

Rank	ICAO	Total Charging (kWh)	Percentage (%)	Airport Name
1	EHAM	458,648	63.0	Amsterdam Airport Schiphol
2	LSZH	44,272	6.1	Zurich Airport
3	LFPG	41,469	5.7	Paris Charles de Gaulle Airport
4	LFSB	39,270	5.4	EuroAirport Basel Mulhouse Freiburg
5	EKCH	30,977	4.3	Copenhagen Airport, Kastrup
6	EDDM	22,230	3.1	Munich Airport
7	LSGG	21,982	3.0	Geneva Airport
8	EGCC	20,335	2.8	Manchester Airport
9	EBBR	13,200	1.8	Brussels Airport
10	EKBI	7,170	1.0	Billund Airport

Table 15. Annual summary of electric aircraft charging requirements and infrastructure utilization across European airports (2015–2024).

Metric	Value (Annual)
Total energy charged	6.5M – 10.7M kWh
Number of airports with charging	25 – 30
Average per active airport	258k – 372k kWh
Top airport (EHAM)	3.1M – 5.5M kWh

Table 16. Annual operational volume measured in total flight legs and average legs per aircraft for a 10-unit E9X fleet.

Year	Total Legs	Avg Legs per Aircraft
2015	7,628	762.8
2016	7,798	779.8
2017	7,894	789.4
2018	8,010	801.0
2019	8,068	806.8
2020	2,245	690.8
2021	1,953	756.0
2022	5,239	776.1
2023	7,478	780.3
2024	7,876	787.6
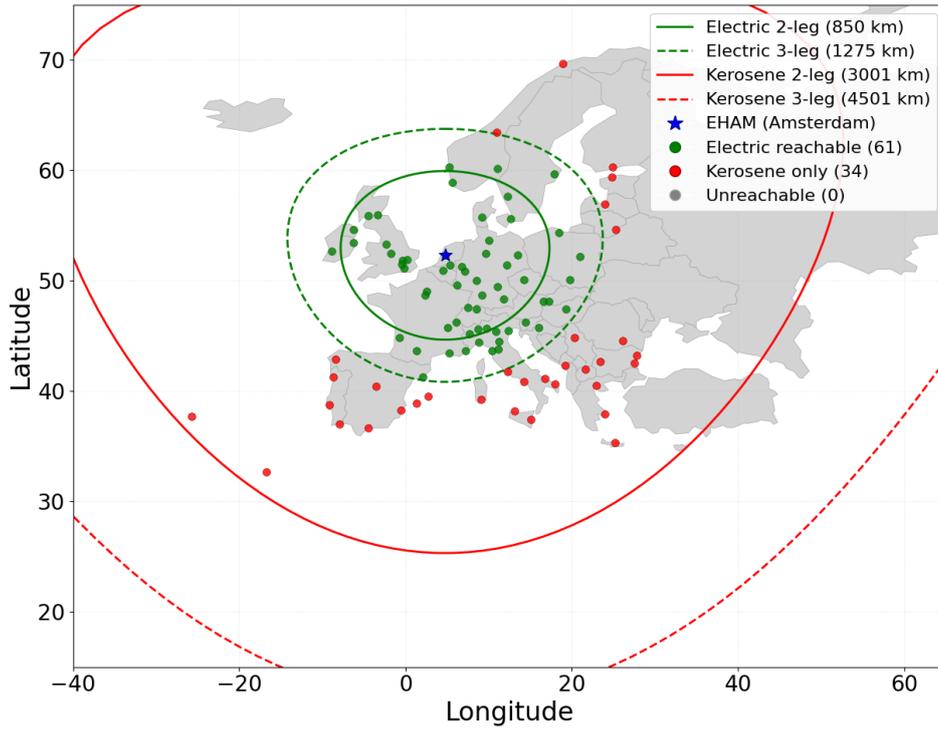
Figure 25. Maximum Effective Range (E9X vs. ERJ-175). Map visualizing the operational reach from the central hub for electric and kerosene aircraft allowing for 2 or 3 stops.

(a) 2019-06 Electric

(b) 2020-06 Electric

(c) 2024-06 Electric

(d) 2019-06 Kerosene

(e) 2020-06 Kerosene

(f) 2024-06 Kerosene
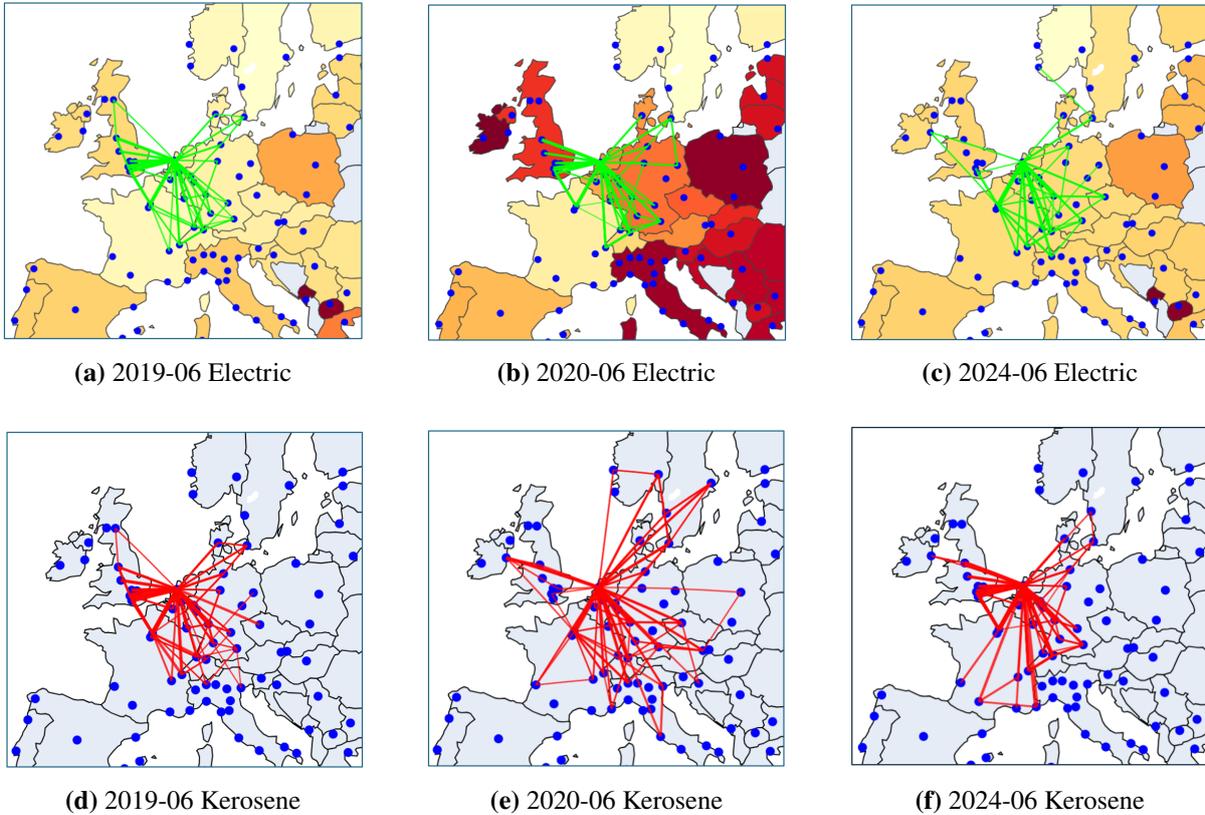
Figure 26. Optimal networks for June in different years. The background color in electric plots shows more expensive electricity countries as darker reds.

C. Charging Strategies (RQ1)
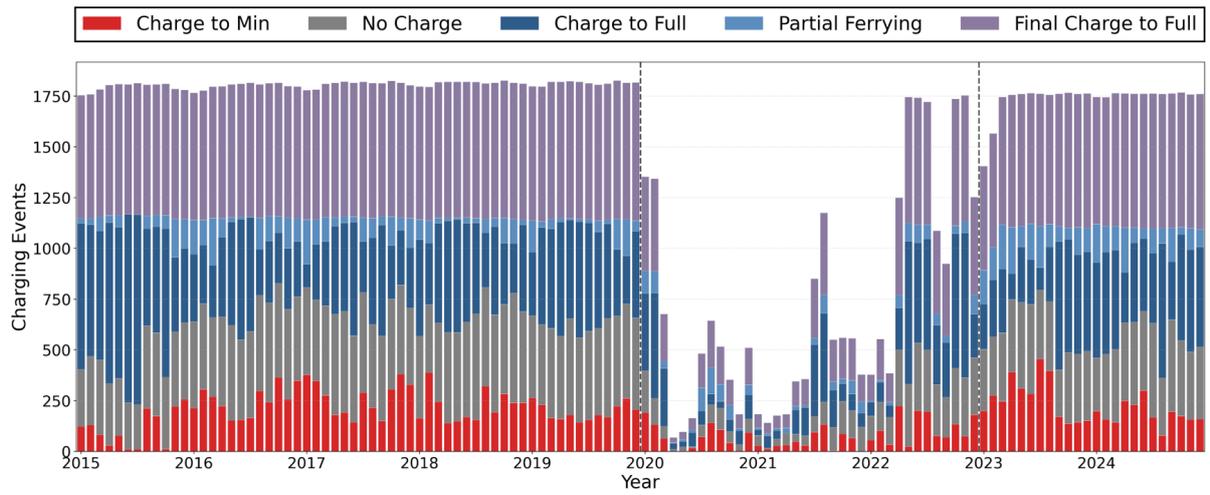
Figure 27. Charging Decisions Over Time (2015–2024)

D. Value of Knowledge (RQ2)

This appendix provides supplementary results for Research Question 2, quantifying the value of including electricity price information in strategic planning. The results are divided into two sections: a) the general value of price awareness (knowing it at all), and b) the sensitivity to price magnitude (knowing how much).

Value of Knowing It At All: Price Awareness

This section compares the performance of the *Average Price* and *Agnostic* planning models against the *Perfect Information* benchmark. Figure 28 displays the performance metrics specific to the stable pre-COVID period, while Figure 29 presents the results over the full 120-month dataset. Table 17 summarizes the statistical performance across all defined market periods.

(a) Profit % (Detail) **(b)** Profit % (Full) **(c)** Profit (EUR)

(d) Cost % (Detail) **(e)** Cost % (Full) **(f)** Cost (EUR)
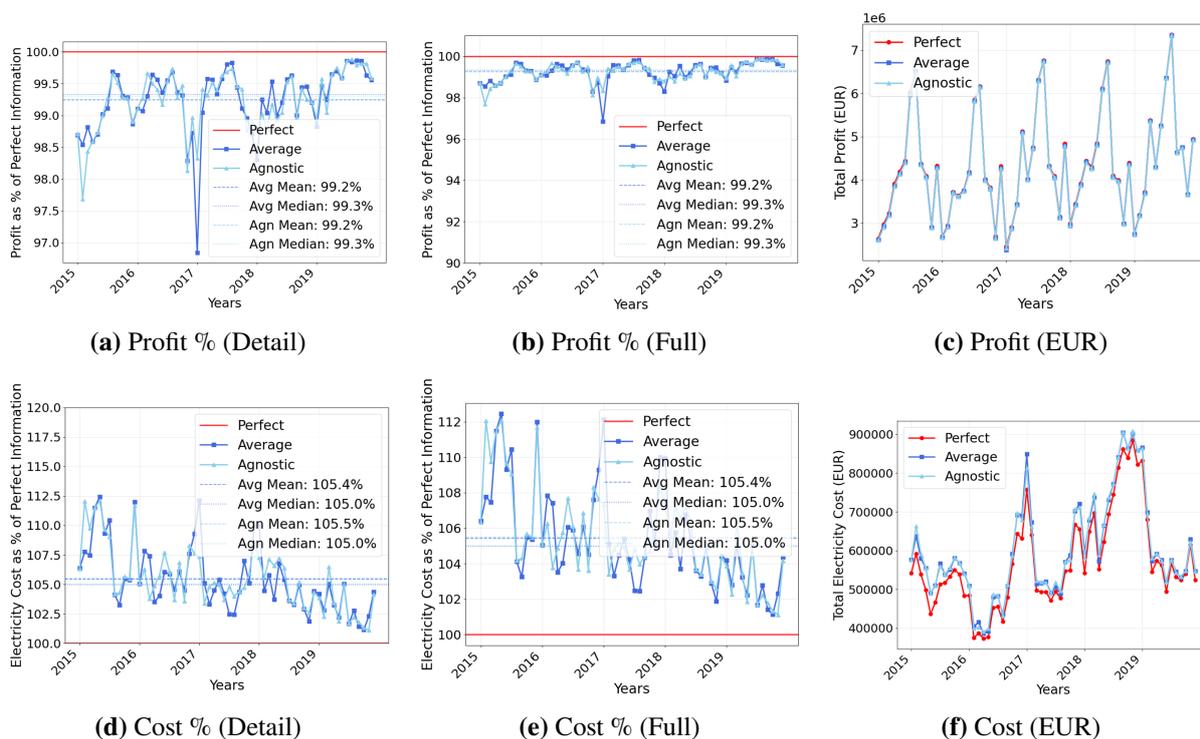
Figure 28. Performance metrics during the Pre-COVID period (2015–2019). Top row (a–c) displays profit relative to the perfect information benchmark and in absolute values. Bottom row (d–f) displays the corresponding electricity costs.
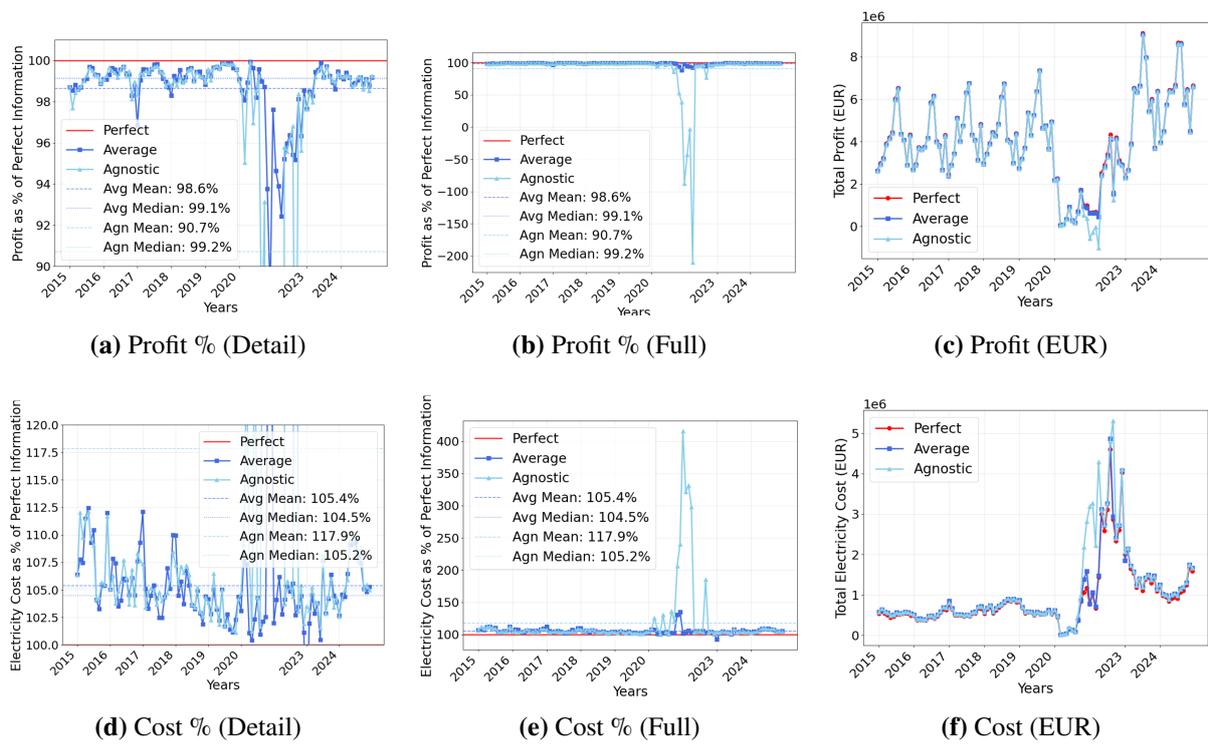
Figure 29. Performance metrics over the full 120-month dataset. Top row (a–c) displays profit relative to the perfect information benchmark and in absolute values. Bottom row (d–f) displays the corresponding electricity costs.

Table 17. Relative profit and electricity cost performance for imperfect information models across different time periods.

Model	Profit		Electricity Cost	
	Mean	Median	Mean	Median
Full 120-Month Period				
Average Price	98.6%	99.1%	105.5%	104.5%
Agnostic Price	88.8%	99.0%	123.4%	105.7%
Pre-Corona Period				
Average Price	99.2%	99.3%	105.8%	105.4%
Agnostic Price	99.2%	99.3%	105.6%	105.5%
Corona Period				
Average Price	97.3%	98.5%	105.7%	103.5%
Agnostic Price	64.8%	95.6%	165.3%	117.4%

53

Value of Knowing How Much: Decomposition and Magnitude

This section breaks down the source of value in the planning process and analyzes the sensitivity of the model to forecasting errors regarding the magnitude of electricity prices. Figure 30 illustrates the risk of over- versus under-estimating prices.

(a) Relative Profit Loss   **(b)** Relative Electricity Cost
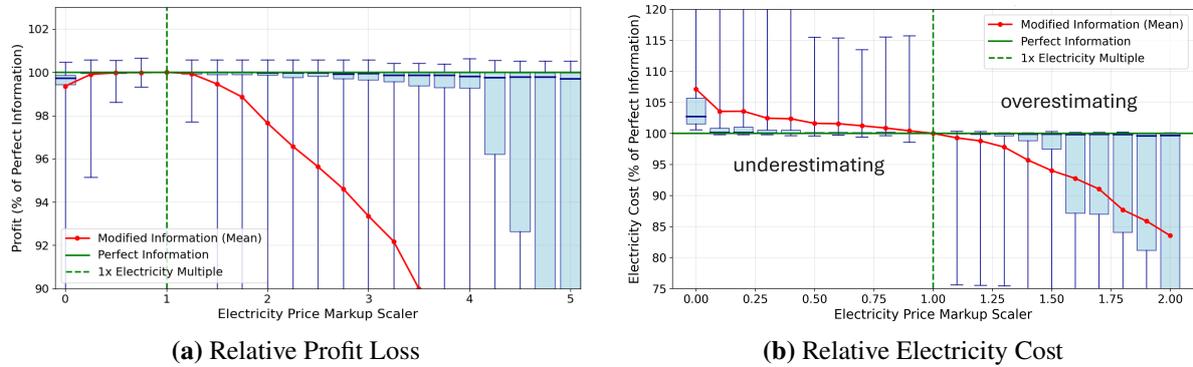
Figure 30. Performance sensitivity to Electricity Price Markup (2015–2024). Box plots displaying (a) relative profit retained and (b) relative electricity costs compared to a perfect forecast benchmark, with prices adjusted by factors ranging from 0x to 5x.

E. Mixed Fleet Assignment (RQ3)

This appendix provides supplementary results for Research Question 3, analyzing the Mixed Fleet Assignment Problem. The supporting plots are divided into two sections: a) unconstrained mixed fleet and b) constrained mixed fleet.

Unconstrained Mixed Fleet

The following tables compare the performance of an unconstrained mixed fleet against a homogeneous electric or kerosene fleet. Table 18 compares the financial performance against both homogeneous fleets, while Table 19 shows the percentage gains against the best homogeneous fleet for each month. Finally 20 presents the coefficient of variation in the profit for all three fleet types.

Table 18. Mean Monthly Profit comparison: Unconstrained Mixed Fleet vs. Homogeneous Fleets.

Period	Electric (E9X)	Kerosene (ERJ)	Mixed (Unconstrained)	Improvement vs. Electric	Improvement vs. Kerosene
Pre-COVID	€4.30M	€4.19M	€4.35M	+1.15%	+3.92%
COVID	€1.34M	€2.25M	€2.25M	+67.38%	+0.03%
Post-COVID	€5.90M	€6.03M	€6.14M	+4.00%	+1.81%
All	**€3.74M**	**€3.98M**	**€4.08M**	**+9.20%**	**+2.62%**

Table 19. Frequency of financial gains by the Unconstrained Mixed Fleet compared to the best performing pure fleet for that specific month.

Period	Months with Gain > 0.1%	Percentage of Total	Mean Gain (in those months)
Pre-COVID	12/60	20.0%	0.34%
COVID	2/36	5.6%	0.63%
Post-COVID	6/24	25.0%	0.64%
All	**20/120**	**16.7%**	**0.46%**

Table 20. Coefficient of Variation (CV) in Monthly Profit: Risk comparison across strategies.

Period	Electric (E9X)	Kerosene (ERJ)	Mixed (Unconstrained)
Pre-COVID	27.42%	25.08%	26.06%
COVID	88.24%	86.93%	86.89%
Post-COVID	29.69%	25.78%	26.34%
All	**57.09%**	**49.94%**	**50.25%**

Constrained Mixed Fleet

This section analyzes fixed fleet compositions ranging from 0% to 100% electric, maintained throughout the 120-month period. Figure 32 details the structural impact of electrification on profit margins, route selection, and leg distances. Figure 31 maps the risk-return curves for a 10-aircraft fleet for all three time periods in a single plot to show the correct placement of each curve.
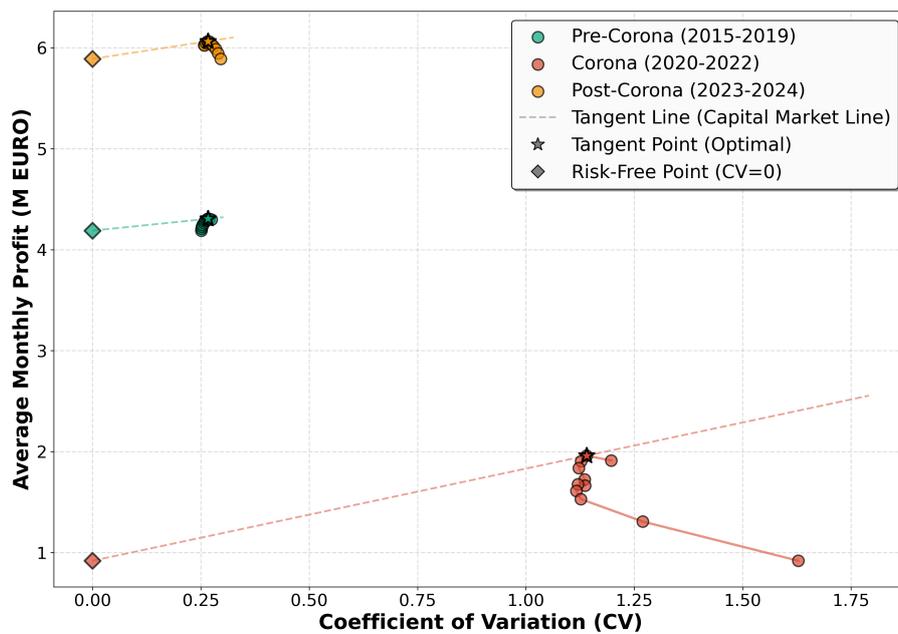
Figure 31. Risk-Return Profiles (Fleet Size 10). Scatter plots showing Mean Profit vs. Coefficient of Variation (CV) across three time periods. The star indicates the optimal portfolio on the Capital Market Line.
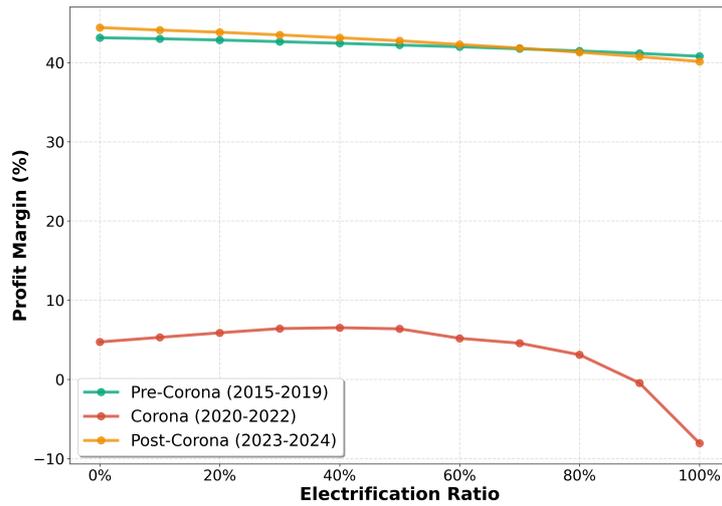
(a) Profit margins per period.
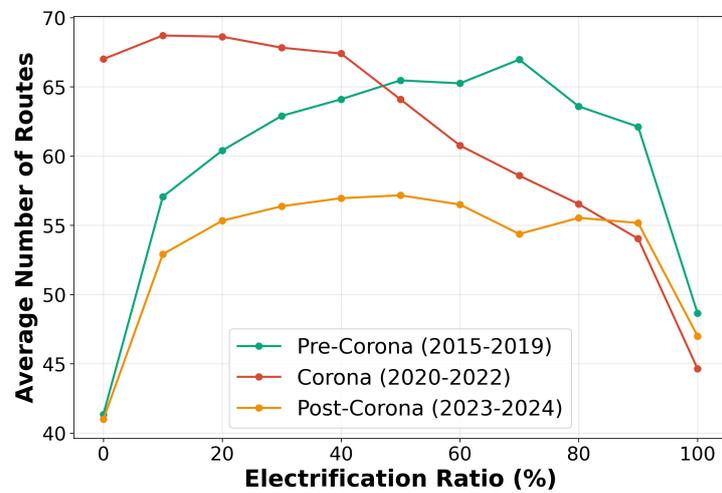
(b) Total routes served (Electric + Kerosene).
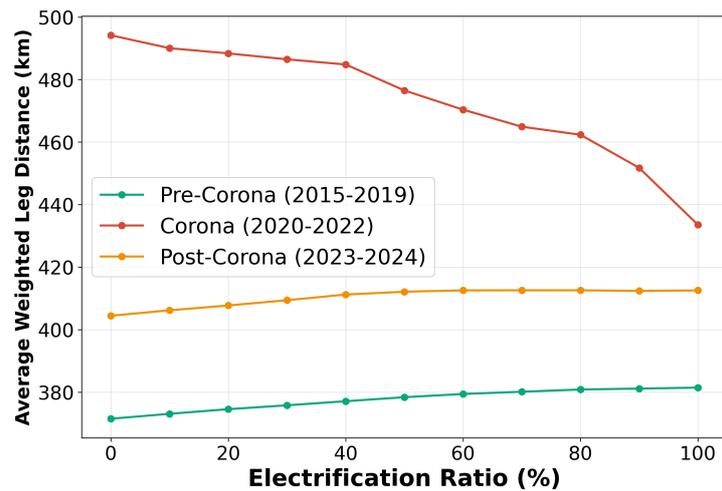
(c) Frequency-weighted average leg length.

Figure 32. Constrained Mixed Fleet Performance Breakdown (Fleet Size 10). Analysis of operational metrics across different fixed electrification ratios.

Part I

Supporting Work

| Year | Author | Airline Planning Problem | | | | Method | Model Fidelity | | | Uncertainty | | Aircraft | | |
		Network Design	Route Frequency	Fleet Assign.	Flight Scheduling		Local Fuel Costs	Varying Fuel Costs	Varying Demand	Uncertain Fuel	Uncertain Demand	Fleet Type	Range	Charge Siting
2024	C. Leenawong et al	✓		✓		MILP (binary)	✓					Conv.	Long	
2024	F. Vehlhaber et al					MPC, MILP (receding horizon)	✓	✓				Elect.	Short	All
2024	A. Kinene et al	✓	✓	✓	✓	MILP			✓			Mixed	Short	Optimized
2024	J. Westin et al	✓	✓		✓	MILP (network flow model)						Elect.	Very Short	All
2023	T. de Jesus et al		✓	✓		MILP						Conv.	Medium	
2023	P. Proesmans et al		✓	✓	✓	DP			✓			Conv.**	Long	
2023	B. Chan et al			✓		MILP (time-space network)						Mixed***	Short	
2023	M.Liu et al			✓		MILP (two-stage)		✓	✓	✓	✓	Conv.	Long	
2023	A. Kinene et al	✓				MILP, KS Heuristic						Elect.	Short	Optimized
2023	F. Vehlhaber et al			✓	✓	MILP (time-space network)	✓*	✓				Elect.	Very Short	All
2022	C. Justin et al	✓	✓	✓	✓	MILP			✓			Mixed*	Short	All
2022	M. Faa	✓				-						Mixed	Short	Optimized
2022	M. Mitici et al				✓	MILP (two-phase)			✓			Elect.	Very Short	Hubs only
2021	V. Özkır et al			✓	✓	Heuristic (two-phase), Integer Programming						Conv.	Medium	
2021	A. Ham et al				✓	MIP, CP		✓				EV Cars	Very Short	
2021	V. Özkır et al	✓		✓		MILP (two-phase) & Heuristic (two-phase)						Conv.	-	
2020	C. Justin et al					Linear Programming (Network Flow Model)	✓					Elect.	Very Short	All
2019	M. Pereira et al				✓	MILP (two-stage)						Both	Very Short	All
2013	C. Hsu et al		✓	✓		MILP		✓	✓	✓		Conv.	Long	
2013	M. Naumann et al	✓	✓			MILP (two-stage)		✓	✓	✓	✓	Conv.	Long	
2013	C. Hsu et al			✓		MILP		✓	✓	✓		Conv.	Long	
2012	A. Kheraie et al	✓		✓	✓	MILP (flight string)	✓					Conv.	Short	
2012	M. Naumann et al		✓	✓		MILP (two-stage)		✓	✓	✓	✓	Conv.	Long	
2002	C. Hsu et al		✓			NLP			✓		✓	Conv.	Long	
	Deterministic Analysis Model	✓	✓	✓		MILP (2-stage / integrated)	✓	✓	✓			Mixed	Short (E9X)	All
	Continuous Improvement Model	✓	✓	✓		MILP, two-phase heuristic	✓	✓	✓	✓	✓	Mixed	Short (E9X)	All

*Account for local electricity production
but not local grid prices

* Mixed Conv., Hybrid, and Electric

** Climate optimized design

*** Mixed Conv. And Hybrid only

Both = Only Elect. vs. Only Conv.

Mixed = Conv & Electric

F. Assumptions and Limitations

To maintain a clear focus, this study adopts a set of simplifying assumptions and acknowledges several limitations. These are categorized into model scope and formulation, operational and physical factors, and data and economic parameters.

Model Scope and Formulation

- *Profit-Maximization Objective:* The model assumes the airline's primary objective is profit maximization, which provides a clear and standard economic performance metric for strategic analysis. It does not co-optimize with other goals, such as maximizing market share, passenger welfare, or environmental goals.

- *Exogenous and Inelastic Demand Model:* Passenger demand is treated as an exogenous and inelastic input. This means it does not respond to the model's output, such as the generated flight frequencies or aircraft types. Furthermore, the framework models a single airline in isolation and does not account for competitive reactions from other carriers. This simplification is justified by the strategic scope of the analysis and is a reasonable starting point for modeling the introduction of a novel aircraft technology, which would initially capture a small market share. However, in reality, elastic demand will likely have a significant impact.

- *Strategic Scope and Monthly Granularity:* The model operates at a strategic level with a monthly planning horizon, focusing the analysis on high-level decisions such as network design, frequency planning, and fleet assignment. Consequently, it omits subsequent operational layers (e.g., detailed aircraft routing, maintenance scheduling, crew pairing) and does not capture finer-grained dynamics like intra-day electricity price volatility. This strategic abstraction is standard practice to ensure computational tractability and aligns with the granularity of available demand data. While appropriate for a strategic study, it is acknowledged that constraints emerging from the excluded operational layers could slightly alter the final optimal network structure.

- *Variable Fleet Size:* The model is formulated with a variable fleet size, capped at 10 aircraft, allowing the total number of aircraft to change monthly. While this was intended to identify the theoretically optimal fleet size for given market conditions and to focus the network on the most profitable routes, it introduces a key limitation. It allows the model to unrealistically shed fixed ownership costs by reducing the fleet size month-to-month, a flexibility not available to a real-world operator with committed assets. In retrospect, a more robust formulation would impose a fixed fleet size, forcing the model to maximize profit against the sunk costs of the entire fleet and thereby providing a more accurate simulation of an airline's strategic reality

Operational and Physical Factors

- *Hub-Centric Network Structure:* The model is constrained to a single-hub network architecture, where all routes are cycles originating and terminating at a designated hub. This is a deliberate choice to model a plausible initial deployment strategy for a new aircraft type but is a limitation as it precludes the discovery of potentially more profitable point-to-point or multi-hub network structures. Also note that these hubs might not necessarily be the same major hubs we observe today (e.g., AMS), reflecting a potential shift in optimal network configurations for electric aircraft due to range and charging considerations.

- *No Maintenance:* Aircraft maintenance requirements are abstracted into the overall monthly aircraft productivity metric (available block hours) and the CASK. This oversimplifies complex maintenance routing logic, which is a separate operational problem, allowing the model to focus on the strategic network response to energy prices.

- *Uniform Charging Infrastructure:* All large airports are assumed to be equipped with sufficient charging infrastructure. The high demand for electric aircraft will make this a definite constraint which must be

further explored.

- *Unconstrained Charging Capacity and Rates:* Airports are assumed to have unlimited charging capacity, meaning there is no constraint on the number of aircraft that can be charged simultaneously or on the maximum charging rate based on airport infrastructure. This simplification isolates the impact of energy price from the impact of infrastructure congestion and charging rate limitations, but it limits the model's ability to reflect real-world variations in airport charging capabilities. The results in Table 15 show that a fleet of 10 E9X aircraft charged between 258 and 372 MWh per year. The hub airport (EHAM) is much higher with 3.1–5.5 GWh. Considering that a typical large airport uses in a year between 100–300 GWh now [87] this number is actually quite modest. However, this is only for a fleet of 10 medium-range electric aircraft.

- *Full Charge Requirement at Hub Airport:* The model enforces a full charge state at the beginning and end of each route cycle at the hub airport to ensure continuity. This constraint precludes partial charging or no charging at the hub airport (at the end of a route), limiting the model's ability to optimize the charge level based on the minimum required for the next flight leg (which does not exist at the end of a route). While the model allows some flexibility through overcharging (charge ferrying) at previous airports in the route, the full charge requirement at the hub airport slightly restricts overall charging optimization. Incorporating this into the model in a way that would ensure continuity between aircraft locations and charge states would require aircraft routing which is outside of the strategic scope of this research.

- *Linearized Physical Processes:* Several non-linear physical processes are linearized. These include modeling energy consumption with a constant specific metric (kWh/km) and charging dynamics. The linear charge curve was deemed acceptable due to the 10 and 95% SoC constraints. Non-linear charging primarily affects SoC above roughly 90% [52], meaning only the last 5% is inaccurate. With a total charging time of 45 minutes, the difference in slope likely accounts for only a few minutes.

- *Constant Load Factor:* A constant load factor of 78.6% is applied across all months while real load factors vary per month, per airline, per route, and per aircraft type.

- *No Battery Degradation:* Battery capacity degradation over its lifecycle is not modeled. Table 16 shows that the mean number of legs per year per aircraft is 773.1, or approximately 61 flights per month (2 per day). If an electric aircraft battery requires replacement every 1000-2000 cycles [88, 89], replacement could be needed every 1.3-2.6 years.

- *Standardized Flight Operations:* Standardized flight operations, including a constant route lengthening coefficient and uniform flight profiles, are assumed to provide a consistent baseline for performance comparison across all scenarios. Real-life operations have route-dependent flight profiles and uncertain delays. Furthermore, the equal maximum operating time for electric and kerosene-powered aircraft could be explored further. The low noise profile of EA could allow for longer operating hours.

- *Kerosene Reserve Fuel:* Unlike the electric aircraft, which is constrained by a 10% minimum SoC, a specific reserve range buffer was unintentionally omitted for the kerosene fleet. This omission is considered to have a negligible impact on results. The optimized network is constrained by the shorter range of the electric aircraft and the maximum route length settings, resulting in flights well within the ERJ-175's 3,334 km range. Consequently, even with a standard fuel reserve, the kerosene aircraft would not face range limitations on the selected routes.

Data and Economic Factors

- *Exclusion of Power-Based Charges:* The model excludes power-based demand charges (e.g., costs based on peak MW draw), focusing solely on energy costs (€/MWh). This isolates the impact of spatiotemporal energy price variations, while the challenge of peak power scheduling has been addressed in prior research [53, 90], including power-minimizing approaches.

- *Exclusion of Carbon Pricing:* The economic analysis does not include the costs or benefits of carbon pricing policies, such as the EU Emissions Trading System (ETS) which could make EA more attractive [91]. This provides a clear economic baseline based purely on operational energy costs. The framework could be extended in future work to determine the carbon price at which electrified aviation becomes more competitive.

- *Aggregated Pricing Data:* To ensure data availability, electricity prices are sourced at a country-level, monthly-average basis. This is a key limitation, as it averages out both sub-national price zones and significant intra-month volatility, which are crucial drivers of operational cost-saving in reality. Kerosene prices are modeled at a continent level and thus come with similar limitations. Kerosene prices exhibit limited spatial variation between countries, however, there is undoubtedly some difference. Unfortunately, such data is not available, so the continent-wide monthly average is used.

- *Historical Data as Future Proxy:* The analysis uses historical demand and price data (2016-2022). This provides a realistic, validated baseline for current market conditions,w but does not extrapolate to the E9X's planned 2033 introduction, thereby not accounting for future market dynamics.

- *EU Countries:* The dataset includes electricity prices for 31 of 47 European countries. We have excluded peripheral island nations (Cyprus, Malta, Iceland), Western Balkan states, and microstates. These excluded regions are geographically remote from Central Europe, which is the primary focus of this study, and possess limited domestic demand. Consequently, their lack of inclusion does not significantly compromise the findings regarding the central European electricity market.

- *Simplification of Yield and Cost Factors:* To manage complexity, this study minimizes variables: revenue uses a single yield per passenger-km, costs are grouped into energy, fixed (to deter marginal aircraft use), and one operational factor for all ancillary expenses. This enables easier validation of aggregated factors and ensures a consistent level of detail across the financial model, however it can oversimplify costs. Future papers could add route-specific costs, such as airspace charges and airport-specific fees, in order to better represent the financial pros and cons of a specific route.

- *Unequal Months:* We use monthly electricity and kerosene prices and therefore adhere to a strictly monthly time granularity for all results. However, months are not equal in days, so comparing results such as monthly profit is not a fair comparison. A better approach would be to use 13 4-week blocks, but the data would have to be aligned to be able to do this.

- *Inflation Adjustment:* To align all fiscal factors to the same timeframe, many are inflation-adjusted. Aircraft auxiliary operating costs are adjusted to the simulation month using a general inflation factor and yields via HCIP. Electricity and kerosene prices, reported in their monthly currency, require no adjustment. This ensures each month uses period-correct values. However, it is essential to note that the results are reported in *that* month's EURO, so profits over time will include inflation. While many experiments compare months to themselves (yielding relative performance), not all do. Results were not re-inflated to 2025 EUROs to avoid hidden bugs, especially when re-evaluating models with electricity prices.

G. Sensitivity Analysis

This appendix presents a comprehensive sensitivity analysis to assess the robustness of the model and identify the primary drivers of airline profitability and network structure. By systematically varying key input parameters and observing the impact on the model's outputs, we gain deeper insights into the underlying economic and operational dynamics. The analysis is structured into four main categories. These include a general overview of high impact parameters, an examination of model specific configuration parameters and their effect on runtime, an evaluation of external environmental factors, and an exploration of critical aircraft design parameters.

General Sensitivity Analysis

We conducted a sensitivity analysis where key parameters were individually adjusted by ±10 % from their baseline values. The results are summarized in Table 21 and highlight the model's primary economic drivers. Note that this method of sensitivity analysis does not account for covariance effects.

The model's output is most sensitive to the Yield Curve Scaler and Load Factor. A ±10 % perturbation in either parameter drives a substantial profit change of approximately ±22 % and ±19 % respectively. Aircraft productivity, measured by the number of Seats and available Hours per Month, along with direct Operating Costs, also rank as primary drivers of financial performance. In contrast, the model exhibits significantly lower sensitivity to parameters specific to electric aviation such as Charging Rate and Charge Setup Time. Notably, a ±10 % change in Aircraft Range alters profit by only ~1.4 %, likely due to the model's preference for short routes.

Table 21. Sensitivity of Total Profit to ±10 % Parameter Perturbations

Parameter	Base Value	–10 % (%)	+10 % (%)
High Impact Parameters (>5 %)			
Yield Curve Scaler	0.4	–22.28	+22.53
Load Factor (LF)	0.786	–19.21	+19.16
Seats (E9X)	90	–10.12	+10.02
Operating Cost (€/pax-km)	0.095	+9.60	–8.60
Hours per Month	315	–8.59	+8.45
Medium Impact Parameters (1–5 %)			
Aircraft Speed (km/h)	648	–4.57	+4.39
Demand Scaler	0.1	–3.37	+3.11
Min Turnaround Time (h)	0.5	+2.39	–2.12
Fixed Cost per Month (€)	115,329	+2.01	–1.43
Aircraft Range (km)	1,000	–1.60	+1.27
Electricity Markup	1.4	+1.46	–1.39
Battery Capacity (MWh)	15.0	+1.20	–1.43
Low Impact Parameters (<1 %)			
Charge Setup Time (h)	0.25	+0.12	–0.33
Min Profit Margin	0.1	+0.19	–0.14
Min SOC	0.1	+0.04	+0.02
Charging Rate (MW)	20.0	–0.02	+0.07
Max SOC	0.95	+0.00	–0.04
Route Lengthening Factor	1.07	+0.00	+0.00

Notes: Values reported as % change in total profit from the baseline of €6,665,350. Parameters are ordered by descending average absolute impact within each category. The test was run for an E9X fleet in a single month (June 2024).

Model Configuration & Runtime

This section analyzes how computational constraints and fleet configurations influence the model's solve time. Understanding these sensitivities is crucial for justifying the structural limitations imposed on the network such as the number of permissible intermediate stops.

Fleet size and type effect on runtime

The model's runtime is more sensitive to fleet composition than to fleet size as shown in Figure 33. Pure electric fleets yield the fastest computations because their limited range constrains the set of feasible routes and simplifies the optimization problem. Conversely, the longer range of kerosene aircraft expands the potential route network which leads to a moderate increase in runtime. Mixed fleets consistently require the most time. This is attributed to the added combinatorial complexity of assigning the optimal aircraft type, each with unique constraints, to every potential route. This makes the optimization inherently more difficult for the solver. The peaks in electric fleet runtime can be considered outliers that only occur at specific fleet sizes.
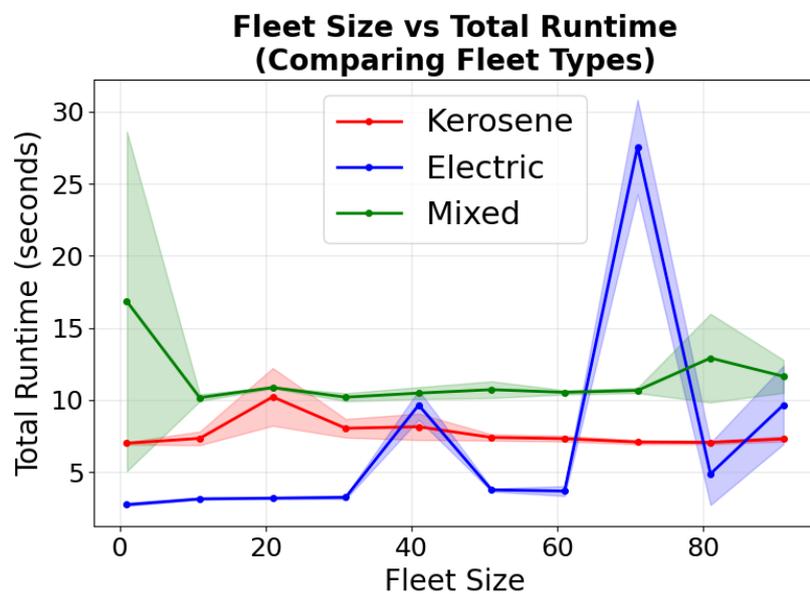
Figure 33. Model Runtime vs. Fleet Size. Line graph comparing computational runtime for pure kerosene, pure electric, and mixed fleets of varying sizes.

Intermediate Airports

This analysis evaluates the model's sensitivity to the maximum number of intermediate airports allowed in a route. This parameter defines the complexity of the circular routes originating from the hub. A value of one permits only direct flights such as HUB to A to HUB and a value of two allows for multistop routes such as HUB to A to B to HUB. Increasing this limit expands the set of feasible routes and potentially unlocks more profitable markets. However, this expansion leads to a combinatorial increase in candidate routes. For the specific network under consideration, allowing one intermediate airport (two leg routes) generates only 36 candidate routes. This number grows to 762 routes for two intermediate airports and explodes to 22,214 routes for three intermediate airports. This renders optimization computationally infeasible with the current model structure.

Figure 34 illustrates this fundamental tradeoff. The left panel shows that increasing the maximum number of intermediate airports from one to two substantially raises the mean monthly profit from €3.03 million to approximately €4.0 million. This highlights the economic benefit of a more flexible network structure. Conversely, the right panel demonstrates the associated computational burden. The mean runtime escalates from a negligible duration to approximately 14 seconds. While this may seem modest for a single run, it becomes a critical factor in larger experiments which can require 2,520 model executions. This makes such an increase prohibitive for the overall research.

While testing a maximum of three intermediate airports was considered, the exponential growth in the number of routes rendered this option computationally prohibitive. A network restricted to one intermediate airport (direct routes only) proved too rigid and limited its ability to adapt to dynamic conditions such as fluctuating electricity prices. Therefore, a maximum of two intermediate airports was selected as the standard for this study. This value strikes an effective balance. It provides sufficient network flexibility to enhance profitability while maintaining computationally tractable runtimes. It also aligns with a realistic hub and spoke operational model without deviating into complex point to point services that routes with three or more stops might represent.
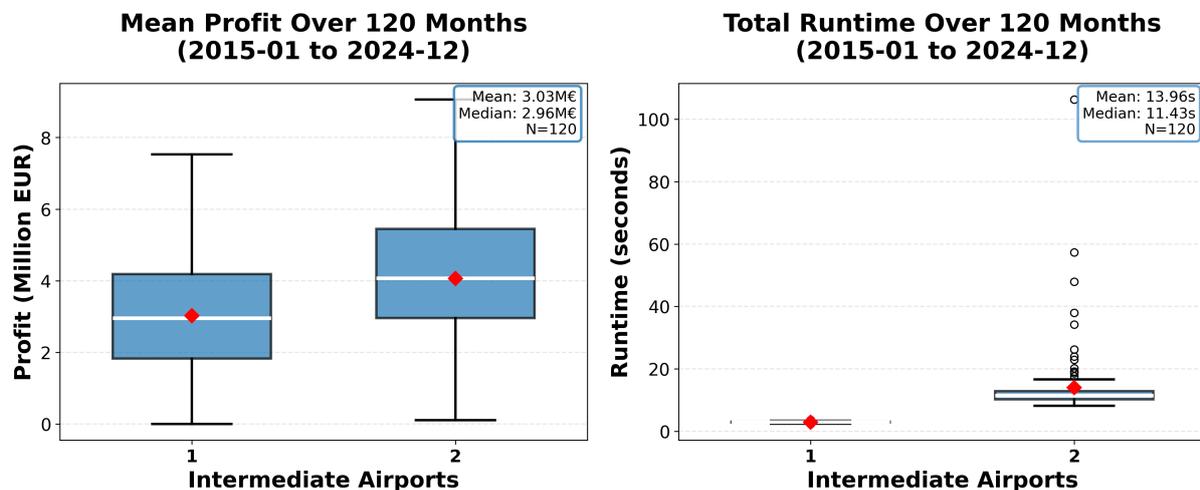
Figure 34. Impact of Intermediate Stops on Profit and Runtime. Box plots comparing mean monthly profit (left) and total model runtime (right) for 1 versus 2 intermediate stops.

Hub Airport Selection

The choice of hub airport fundamentally determines the available route network and potential demand. As illustrated in Figure 35, Amsterdam Schiphol Airport (EHAM) ranks as the 2nd best airport to base Electric Aircraft (EA) operations according to the model. It closely follows the top performer. From a sensitivity analysis perspective, the profits across the top European hubs are not drastically different. This stability indicates that the conclusions drawn from the EHAM case study are broadly applicable to other major EU hubs because the model's performance is not uniquely dependent on the specific geography of Amsterdam.
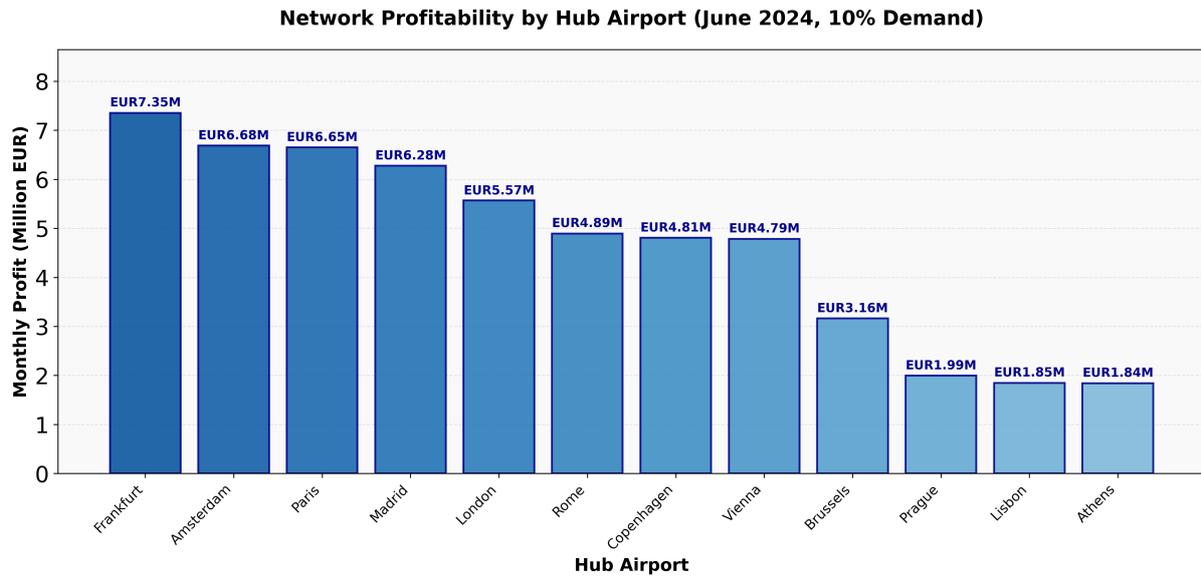
Figure 35. Profit by Hub Airport (June 2024). Bar chart ranking monthly profit for a fleet of 10 E9X aircraft operating from various European hubs.

Environmental Parameters

This section examines how external market forces impact the airline's profitability and strategy. Specifically, we analyze passenger demand saturation, fuel prices, and yield structures.

Demand Scaler (Max Market Share)

The demand scaler parameter governs the maximum market share an airline can capture on any given route. This constraint is necessary to prevent the unrealistic scenario of an airline dedicating its entire fleet to a single route and capturing 100% of the market. The analysis examines the interaction between this parameter and fleet size to evaluate the onset of market saturation and the principle of diminishing returns. As the most profitable short distance routes are utilized first, a fleet that is large relative to the available demand is forced onto progressively less profitable routes. This is illustrated in Figure 36.

As shown in Figure 36a, total network profit increases with both fleet size and the demand scaler. However, the flattening curves at higher scaler values signify market saturation. For any given fleet size, the marginal profit gained from increasing market share from 0.8 to 1.0 is significantly less than from 0.1 to 0.3. Conversely, Figure 36b shows that profit per aircraft is highest for smaller fleets. This is attributed to their ability to be selectively deployed on only the most lucrative routes which maximizes efficiency per aircraft.

This demonstrates a fundamental tradeoff between maximizing total profit, which requires scale, and maximizing efficiency per aircraft, which is more readily achieved by a focused and smaller operation. The model's results are sensitive to this parameter. This is particularly true at lower values where limited demand forces expansion into less profitable markets. For this study, a maximum market share of 10% was selected. This value is considered realistic based on market share data for the top 10 US routes [92]. Furthermore, this 10% scaler ensures that the market is not undersaturated for a representative fleet of 10 aircraft. It compels the model to make more complex network decisions rather than concentrating on a few routes with high demand.

(a) Profit vs. Demand scaler by fleet size

(b) Profit per aircraft vs. Demand scaler
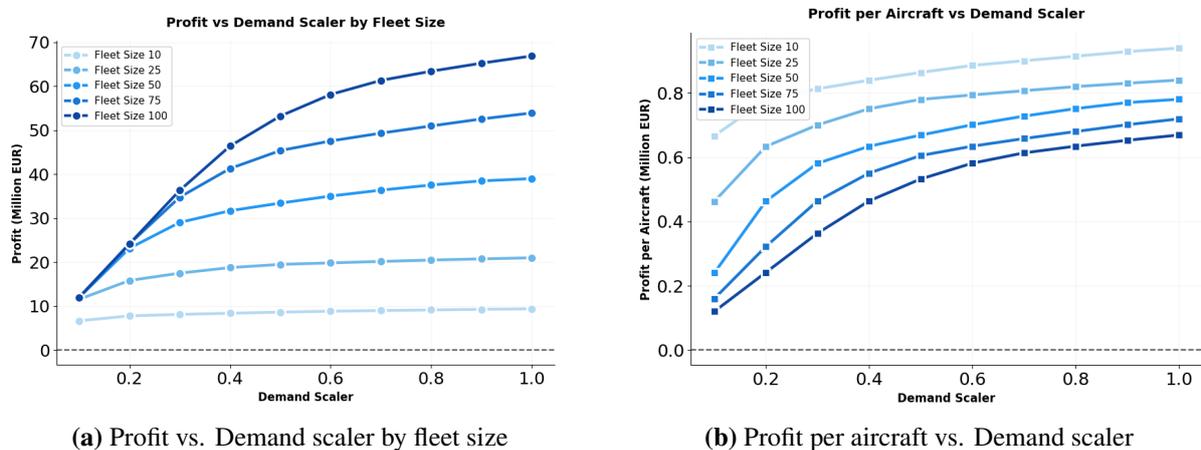
Figure 36. Demand Fleet Saturation. Plots showing (a) Total Profit and (b) Profit per Aircraft as a function of the demand scaler.

Kerosene Price Multiplier

Fuel is a primary driver of airline operational costs and makes profitability highly sensitive to fluctuations in its price.

Sensitivity to Market Price Volatility

In our baseline model, we apply a 1.10x multiplier to kerosene spot prices to account for transportation, fees, and other logistical markups. To test the sensitivity around this assumption, we created a 'Low' scenario with a 20% reduction in the markup (0.88x total multiplier) and a 'High' scenario with a 20% increase (1.32x). As shown in Figure 37, the model exhibits a predictable and linear response to these changes. A 20% decrease in the markup boosts profit by 4.8% to €6.84 million while a 20% increase symmetrically reduces profit by 4.8% to €6.21 million. This linearity suggests that the airline can absorb cost changes from typical market volatility without fundamentally altering its network strategy because the profitability of individual routes remains relatively stable.

Impact of Sustainable Aviation Fuel (SAF)

A separate analysis was conducted to assess the financial impact of transitioning to a 100% SAF powered fleet. Sustainable Aviation Fuel is critical for the industry's decarbonization goals, but its widespread adoption is currently limited by a significant price premium. According to IATA, SAF is approximately 3.1 times more expensive than conventional jet fuel [93]. We modeled this by applying the 3.1x factor to our baseline markup which resulted in a total price multiplier of 3.41x.

The effect on profitability is profound and nonlinear. The profit plummets by 54.0% to just €3.00 million. This disproportionate drop is not merely due to higher fuel expenditures but also a systemic shock to the network. The extreme fuel cost renders a significant portion of the route network unprofitable and forces the model to cease operations on those routes. This leads to a departure from the linear trend seen in the 20% variance cases. An additional profit loss of €200k occurs on top of the increased fuel costs. This underscores that the primary economic barrier to SAF adoption is not just a manageable cost increase but a fundamental challenge to the viability of an airline's established network structure.
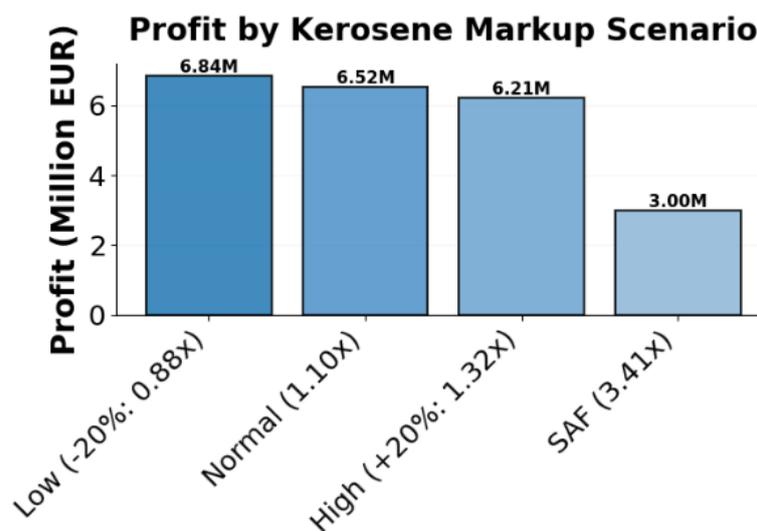
Figure 37. Profit Sensitivity to Kerosene Price Markups. Bar chart comparing network profit under Low, Normal, High, and Sustainable Aviation Fuel (SAF) price scenarios.

Yield Curve and its Impact on Network Structure

The model's revenue is governed by a distance based yield curve (€/pax-km). This dictates that shorter routes command a higher yield per kilometer. As revenue is a primary driver of the network optimization, the model's profitability and strategic decisions are highly sensitive to the shape and magnitude of this curve. We test this sensitivity in two ways: by scaling the existing curve and by replacing it with a flat yield.

Sensitivity to Yield Magnitude

The first test assesses the model's response to uniform shifts in market pricing by applying a linear scaler to the baseline yield curve. This ranges from -30% (a 0.28 scaler) to +30% (a 0.52 scaler). The results presented in Figure 38a show a perfectly linear relationship between the yield scaler and total profit with an R^2 value of 1.0000. The linear trend, given by the equation $Y = 34.47x - 7.13$, indicates that profit is a direct and predictable function of the scaler. This linearity is logical since the model does not alter its fundamental network strategy as long as the relative profitability between routes is maintained. It simply benefits from or is penalized by the overall fare environment.

Sensitivity to Yield Structure

The second test replaces the dynamic distance based curve with a constant flat yield for all routes regardless of distance. This fundamentally alters the economic incentives of the network. Figure 38b reveals a significant nonlinear threshold effect. No profitable network can be established until the flat yield reaches a critical point of approximately 0.15 €/pax-km. This value represents the average breakeven yield required to cover operational costs across the most viable routes. Below this threshold, no flight is profitable. Above it, profit rises rapidly as more routes become viable.

The most profound impact of changing the yield structure is on the optimal network configuration. This is illustrated in the network maps for the kerosene (Figure 39) and electric fleets (Figure 40).

- With the normal distance based yield curve, which offers the highest €/pax-km on short routes, the model prioritizes a dense short haul network centered around the hub. It exploits the high yields of nearby destinations to maximize profit.
- With a flat yield curve, this incentive is removed. The primary driver of efficiency shifts from seeking high yield routes to minimizing the relative impact of fixed costs that generate no revenue. To maximize the proportion of time spent flying, the model favors longer haul flights.

This results in a dramatic strategic shift for the kerosene fleet. The network expands significantly to include much longer routes across Europe. A similar strategic shift is observed for the electric fleet although it is more range constrained. This analysis confirms that the model's output is highly sensitive not just to the magnitude of the yield, but more critically to its underlying structure which dictates the entire network strategy.
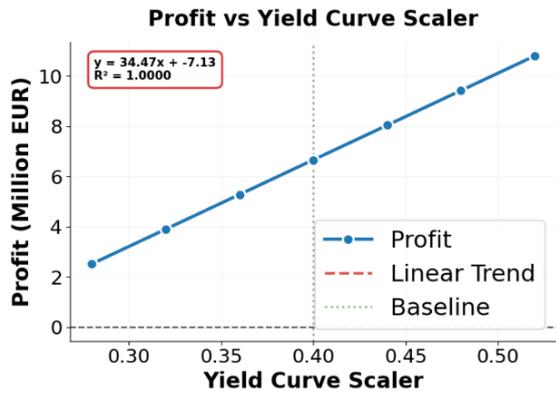
(a) Profit vs. Yield Curve Scaler
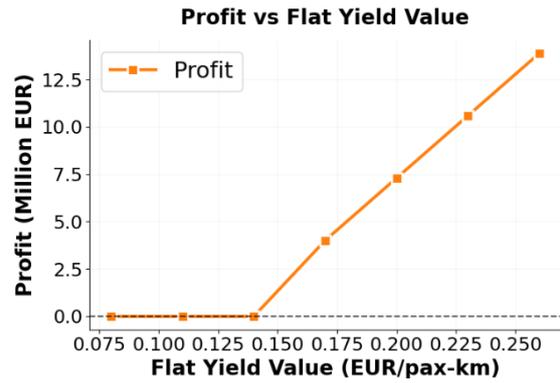
(b) Profit vs. Flat Yield Value

Figure 38. Profit Sensitivity to Yield Curve. Line charts illustrating the impact of (a) scaling yield magnitude and (b) changing to a flat yield structure.
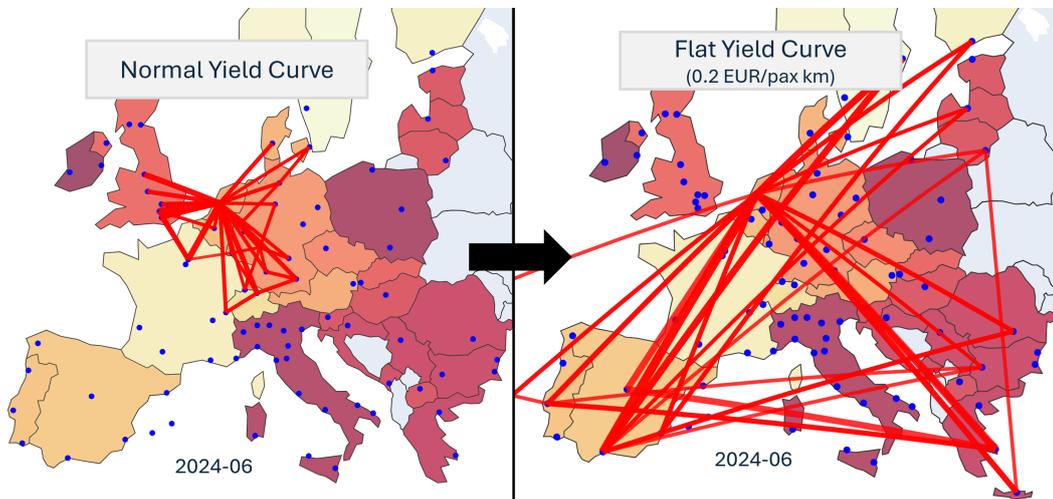
Figure 39. Kerosene Network Structure under Different Yield Models. Maps comparing optimal network topology for a kerosene fleet under distance based versus flat yield curves.
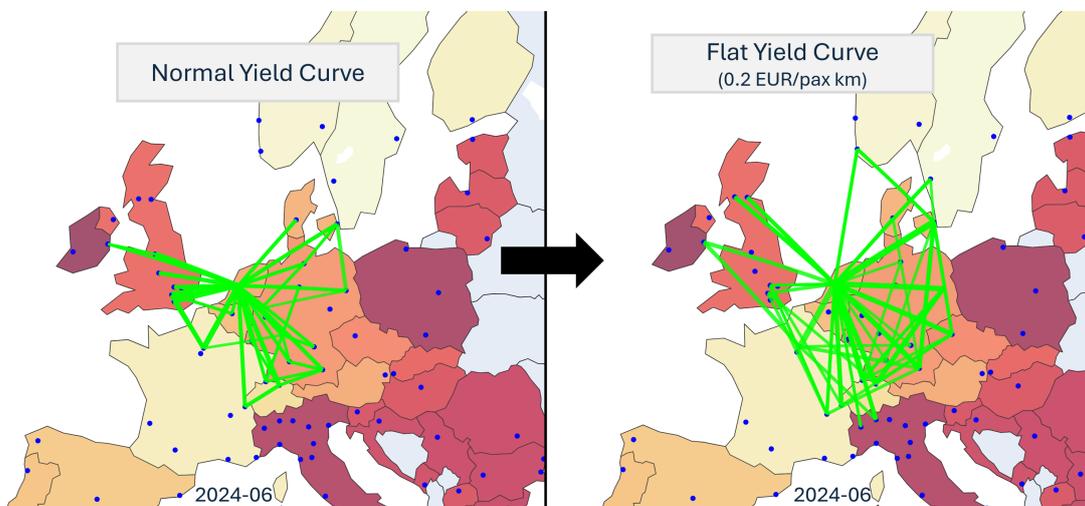
Figure 40. Electric Network Structure under Different Yield Models. Maps comparing optimal network topology for an electric fleet under distance based versus flat yield curves.

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Aircraft Parameters

Range and passenger capacity are two of the most critical design parameters in aircraft development. This section performs a sensitivity analysis on these variables for the E9X. As the E9X is still in its design phase, these parameters are subject to change. This makes this analysis particularly relevant for evaluating potential design tradeoffs.

Aircraft Passenger Capacity

Passenger capacity is a primary design choice for any aircraft and often presents a tradeoff with operational range. Figure 41 illustrates the model's sensitivity to this parameter across different fleet sizes. Profit generally increases with passenger capacity but follows a distinct curve which indicates diminishing returns. While larger aircraft can generate more revenue per flight, their profitability is ultimately constrained by market demand saturation on individual routes. This causes the profit curve to flatten at higher capacities. Larger fleets achieve higher overall profit but follow the same saturation pattern. The baseline capacity of 90 seats is positioned on the steep part of this curve. This suggests that increasing aircraft size is a viable strategy for enhancing profitability until demand becomes the limiting factor.
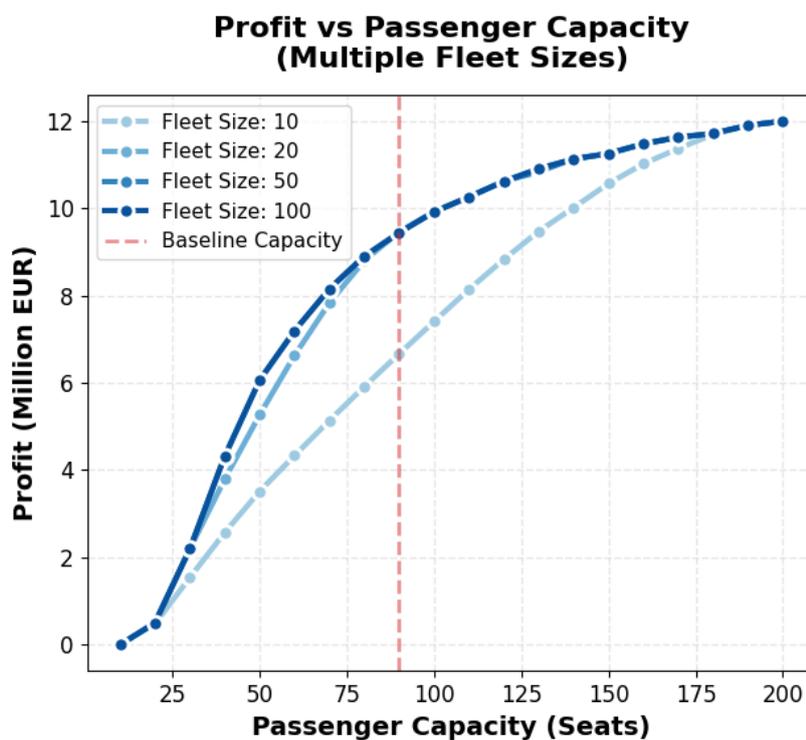
Figure 41. E9X Passenger Capacity Sensitivity. Line chart showing total profit for different fleet sizes as E9X passenger capacity varies from 20 to 200 seats. Note that the curves for fleet sizes 50 and 100 are on top of each other.

Aircraft Range

This section analyzes the model's sensitivity to the E9X aircraft's operational range, a critical parameter whose effects are detailed in Figure 42. As shown in panel (a), profit for larger fleets increases sharply as the range extends from 400 km to approximately 1,200 km, which unlocks more distant markets. However, these gains are subject to diminishing returns and lead to a profit plateau. This saturation point is fleet size dependent. Smaller fleets of 10 to 20 aircraft can be fully utilized on the most profitable short haul routes, causing their profit to level off around 900 km. In contrast, larger fleets of 50 to 100 aircraft require a more extensive network to deploy all assets and thus continue to benefit from increased range up to 1,200 km. Beyond this threshold, the network becomes range saturated, and additional range provides no further economic advantage.

This saturation effect is particularly relevant for future EA airlines. While a limited range is often seen as a key barrier, this analysis suggests its impact is conditional on capturing sufficient market share on shorter routes. A significant volume of profitable short haul traffic already exists that aircraft with reduced range can service. Therefore, the viability of early EA operations could depend more on successful market penetration within a limited radius than on immediate breakthroughs in range technology.

(a) Profit   **(b)** Relative profit
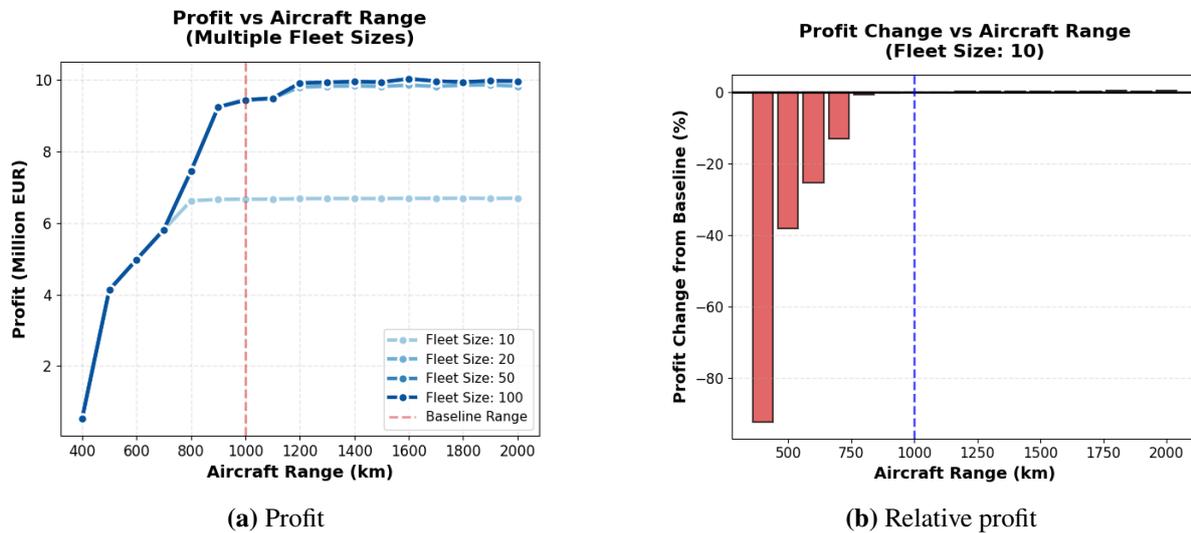
Figure 42. Sensitivity to E9X Aircraft Range. Plots showing (a) Profit, and (b) Profit Relative to a normal run, as aircraft range increases from 400 km to 2000 km.

H. Verification

The following section outlines the verification procedures applied to the model's codebase. Using a controlled, simplified three-node topology, we verified the individual behavioral logic and constraint handling under specific boundary conditions. The results of these tests are summarized below.

Table 22. Comprehensive Model Verification and Validation Test Cases

Category	Test Case	Methodology	Expected Outcome	Result
Basic	Baseline model execution	Run with default parameters.	Model runs without error.	**PASS**
General Aircraft	Verify aircraft range constraint	Set aircraft range to be less than the distance to one node.	The out-of-range node is unreachable.	**PASS**
	Assess impact of increasing operating cost	Increase operating cost per ASK by 2x, 4x, and 6x.	Linear increase in total costs.	**PASS**
	Assess the impact of increasing aircraft seat capacity	Double the number of seats per aircraft.	Number of flights required is halved.	**PASS**
	Verify maximum total fleet size constraint	Set a low 'max_fleet_size' (1-4) with oversaturated (10x) demand.	Demand served increases linearly with available fleet size.	**PASS**
	Verify fleet size constraint per aircraft type	Set a low 'max_fleet_size_per_type' with oversaturated demand.	Reduced flights for the constrained aircraft type.	**PASS**
	Assess impact of increased aircraft speed	Double aircraft speed with oversaturated (10x) demand.	Shorter flight times enable more flights; charging time is the main driver.	**PASS**
	Assess impact of increasing fixed costs	Increase fixed costs per aircraft by 2x, 4x, and 6x.	Profit decreases proportionally to the fixed cost increase.	**PASS**
	Verify minimum demand threshold per route	Set a minimum demand threshold above and below the actual demand for a node.	The route is excluded or included based on the threshold.	**PASS**
Kerosene Aircraft	Assess impact of increased fuel consumption	Increase 'fuel_per_seat_km' for a kerosene aircraft.	Proportionally increased fuel and total costs.	**PASS**
	Assess impact of increased turnaround time	Increase 'kerosene_turnaround_time'.	Fewer flights are possible due to the block time constraint.	**PASS**
	Assess network impact of a localized fuel price spike	Significantly increase the fuel price in one country/region.	Kerosene-based flights are rerouted to avoid the high-cost region.	**PASS**

Table 22 – *Continued from previous page*

Category	Test Case	Methodology	Expected Outcome	Result
Electric Aircraft	Verify minimum SoC on arrival	Set a high 'min_soc' requirement for a long-distance route.	The route is excluded as the 'min_soc' cannot be met.	**PASS**
	Assess impact of charge setup/teardown time	Increase 'charge_setup_teardown_time'.	Lower flight frequencies due to the block time constraint.	**PASS**
	Assess the impact of minimum turnaround time	Increase the minimum turnaround time for electric aircraft.	Fewer flights are possible due to increased time on the ground.	**PASS**
	Assess impact of increased charging rate	Increase the 'charging_rate_mw'.	Shorter charging times, enabling more flights.	**PASS**
	Assess impact of increased battery capacity	Increase the 'battery_capacity_mwh'.	Longer charging times and higher charging costs are required.	**PASS**
	Verify behavior with zero charging rate	Set 'charging_rate_mw' to 0.	No charging is possible; no electric routes are generated.	**PASS***
Airport	Verify airport suitability constraint	Set a specific airport as unsuitable for an aircraft type.	The specified airport is excluded from the network.	**PASS**
	Verify airport placement beyond range	Place an airport just beyond the maximum range of the aircraft.	The airport is excluded due to the range constraint.	**PASS**
	Assess network impact of a localized electricity price spike	Significantly increase the electricity price at one airport.	High-cost airport is avoided for charging and as a destination.	**PASS**
	Assess response to increased demand on a specific leg	Double the demand for routes to/from a specific airport.	More flights are assigned to the high-demand route.	**PASS**
	Verify behavior with missing airport country data	Remove the 'iso3_country' mapping for an airport.	No flights are scheduled to the airport with missing data.	**PASS***
Hyper-parameter	Verify the effective range factor 'r'	Place nodes near the range limit and increase the 'r' factor.	Routes are excluded as the effective range becomes insufficient.	**PASS**
	Verify block time limit	Reduce the maximum 'hours_per_month' for aircraft operation.	Fewer flights are scheduled to stay within the block time limit.	**PASS**
	Verify maximum intermediate airports	Increase 'max_intermediate_airports'.	More complex, multi-leg routes are generated.	**PASS**
	Verify maximum leg distance	Decrease 'max_distance' for a single leg.	Routes containing legs longer than the new maximum are excluded.	**PASS**
	Verify load factor constraint	Increase the minimum load factor (LF) from 0.75 to 1.0.	Fewer flights are scheduled to meet the stricter LF constraint.	**PASS**
	Verify home base change	Change the 'home-base_airport'.	All routes correctly originate and terminate at the new hub.	**PASS**
	Verify zero intermediate airports constraint	Set 'max_intermediate_airports' to 0.	No circular or multi-leg routes are possible.	**PASS***

Table 22 – *Continued from previous page*

Category	Test Case	Methodology	Expected Outcome	Result
Fleet	Assess yield preference for shorter flights	Reduce the distance of one route to make it shorter than others.	Higher yield per km is observed for the shorter flight; it is preferred.	**PASS**
	Verify behavior with high demand and limited fleet	Create oversaturated (10x) demand with a low 'max_fleet_size'.	Fleet is fully utilized, but demand is not fully served.	**PASS**
	Verify behavior with low demand and large fleet	Create low demand with a high 'max_fleet_size'.	Fleet is only partially used; excess capacity exists.	**PASS**
	Verify mixed-fleet (electric/kerosene) assignment	Create a network where costs and range favor different aircraft types.	Fleet usage is balanced based on operational costs and range capabilities.	**PASS**
	Verify fleet assignment by range capability	Create long and short-range routes available to a mixed fleet.	Kerosene aircraft serve long-range routes; electric serve short-range.	**PASS**
General	Verify passenger flow conservation	Create imbalanced demand on a route with intermediate stops.	Passenger flow is conserved across all legs of the route.	**PASS**
	Verify charging decisions logic	Create a multi-leg route requiring an intermediate charge.	Charging behavior correctly meets battery and time constraints.	**PASS**
	Verify circular route generation	–	All generated routes should start and end at the home base.	**PASS**
Savings	Verify behavior with no optimization potential	Set uniform electricity prices across all airports.	No cost savings are achieved through charging optimization.	**PASS**
Extra	Verify behavior with low load factor	Create a low-demand scenario.	The model correctly identifies legs with low load factors.	**PASS**
	Verify behavior with an empty airport list	Provide an empty list of airports to the model.	No routes are generated; model is infeasible.	**PASS***

* = The model failed, but as expected. It failed safely and displayed the correct error message.

- transfer pax approach: The downside of this approach is that it does not capture the different yield profile for transfer passengers compared to direct passengers.

I. Validation

This section presents a comprehensive validation process applied to the core inputs and structural assumptions of the network optimization model. The validation framework systematically evaluates five key domains: passenger demand data, bidirectionality of the demand network, operating cost structures, revenue yields, kerosene cost share, and resulting network topology. In such a model with so many inputs there are definitely more parameters that could be thoroughly investigated but these are most critical or underexplored in the main body of the report.

Demand Data Input Validation

The passenger demand matrix serves as the primary driver of route selection and fleet allocation in the model. It is constructed at a point to point (P2P) level using detailed Eurostat overland passenger flow data for specific airport pairs. To ensure representativeness and accuracy, the processed demand is cross-validated against two independent, high-level benchmarks: (i) aggregate intra-EU and domestic passenger volumes from Eurostat's comprehensive air transport statistics, and (ii) reported traffic at Amsterdam Schiphol Airport (EHAM), a major European hub.

Table 23 summarizes this comparison for 2023. The model estimates 358 million intra EU passengers, closely aligning with Eurostat's reported 349 million a deviation of just 2.6%, which falls well within acceptable bounds for strategic modeling. This strong correlation validates the dataset's fidelity in capturing the dominant intra-EU market segment, which is the primary focus for this research.

In contrast, the model reports only 56 million domestic passengers compared to Eurostat's 146 million. This significant underrepresentation is attributable to data filtering during preprocessing, which excluded smaller regional airports that predominantly serve domestic routes. While this introduces a conservative bias in total addressable market size, particularly for short-haul domestic operations, it does not compromise the study's core objective of evaluating international and cross-border regional routes. A separate validation against EHAM traffic shows 33.5 million passengers to/from Europe in the model versus 42.7 million reported (21.5% underestimation). This gap is reasonable given the model's focus on major commercial airports and its exclusion of long haul and non European flows.

In all, the dataset is deemed robust and suitable for the intended strategic analysis. The conservative domestic estimate may slightly underestimate the total market opportunity, but enhances confidence in the reliability of international flow projections, which are central to the electric aircraft use case. We are satisfied with this validation outcome.

Table 23. Comparison of Annual Passenger Demand in 2023 (millions of passengers) between model-processed data and official sources [94, 95]

Metric	Model (M)	Eurostat/Schiphol (M)
Total Passengers (EU)	422	495
Intra EU Passengers	358	349
National (Domestic) Passengers	56	146
Total Pax to/from Europe (EHAM)	33.5	42.7

Demand Processing Bidirectionality Verification

The model employs a circular-based route optimization framework, which inherently requires operational continuity: every outbound flight from airport A to B must have a feasible return path. This imposes a structural requirement for bidirectional balance in the underlying P2P demand matrix. Due to the construction of the P2P matrix by combining outbound flights from all EU countries, this check is needed after the data processing step to ensure a proper demand matrix.

To verify this property, total annual incoming and outgoing passenger volumes were computed for each airport and plotted against one another. Figure 43 presents this scatter plot, where perfect bidirectionality would place all points along the 45 degree diagonal.

The visualization reveals excellent alignment for the vast majority of airports, with points tightly clustered along the diagonal. A minor deviation is observed for airports in Estonia, which exhibit a small surplus of incoming over outgoing traffic (approximately 600 passengers per month). This imbalance is negligible in absolute terms and geographically peripheral to the primary hub and spoke system under study. It introduces no material constraints on circular formation or fleet scheduling.

Concluding, the demand network satisfies the structural requirements for circular based optimization with high fidelity. The minor imbalance has no discernible impact on model outputs or strategic insights. This verification step is fully satisfied.
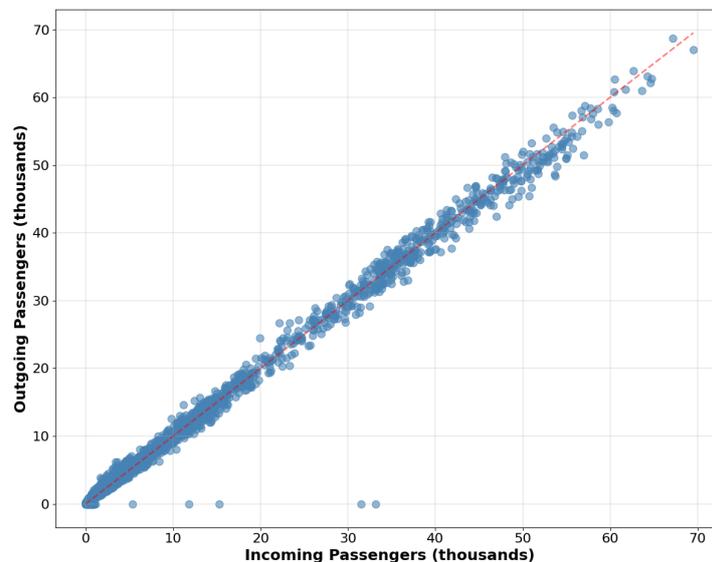
Figure 43. Verification of Demand Bidirectionality. Scatter plot comparing total annual outgoing passengers against total annual incoming passengers for each airport (2015–2024).

Furthermore, following Brexit in September 2020, the UK ceased reporting passenger volumes to Eurostat or any other public database. However, other countries continued to report departures to the UK. Accordingly, post-September 2020 UK demand was reconstructed using the concept of demand bi-directionality by assuming symmetry between incoming and outgoing flows. Historical data from 2015 to 2020 show only a 1.82% excess of incoming over outgoing demand, making a 50:50 ratio a reasonable approximation. Outbound demand was therefore mirrored to estimate inbound volumes.

Operating Costs

Accurate operating cost representation is essential for credible profitability analysis and aircraft selection. The model incorporates three cost metrics per aircraft type: (i) fixed annual cost per aircraft, (ii) variable cost per flight hour, and (iii) cost per available seat kilometer (ASK). All values are normalized to January 2025 EUR using inflation and exchange rate adjustments from 2019 USD.

Table 24 presents the complete cost structure. Conventional narrowbodies show per hour costs of €5,290–5,889 and per ASK costs of 4.39–4.58 ¢, reflecting economies of scale. The smaller EMB 190 has a higher per ASK cost (7.74 ¢) due to reduced seating density. Electric aircraft, despite lower energy costs, exhibit higher per ASK costs (12.4–12.75 ¢) mostly due to being a new technology.

Table 24. Aircraft operating cost metrics, normalized to January 2025 EUR.

Aircraft Type	Per Aircraft Per Year (M€)	Per Flight Hour (EUR)	Per ASK (¢)
A320 Family [82]	15.65	5889	4.39
B737 NG [82]	17.20	5290	4.58
EMB 190 [82]	13.25	4996	7.74
ERJ 175 (model june 2024)	8.77	2320	12.41
E9X 440 (model june 2024)	9.94	2629	12.75

Note: Converted from 2019 USD to 2025 EURO using inflation factor 1.2672 and exchange rate 1.0393 USD/EUR.

In conclusion, while the modeled aircraft exhibit lower fixed and per-hour costs relative to external benchmarks, the values remain within the same order of magnitude. It is worth noting that the model appears to underestimate operating expenses. This slight underestimation is a contributing factor to the high profit margins observed.

Yields

Revenue yield the average revenue per passenger or passenger kilometer is a critical determinant of route profitability. The model uses yield assumptions benchmarked against 2024 financial performance of major European carriers, providing a realistic reference for both full service and low cost operations.

Table 25 reports fleet size, monthly revenue, profit, margin, and per aircraft metrics for six airlines, alongside model projected values for a hypothetical 100 aircraft ERJ 175 and E9X 440 operation. Real world profit margins range from 1.56% (AF KLM) to 14.29% (Ryanair), with per aircraft monthly revenue between €1.84M and €4.56M. In contrast, the model projects operating margins of 46.0% (ERJ 175) and 42.1% (E9X 440), substantially higher than observed. The key difference here is that the model produces pure operating margins instead of the final margin, which would include costs from non-flying-related or support operations, costs our model does not consider. Despite these values being still very high, even in terms of operating margin, with top airlines achieving operating margins only in the 20%'s [96].

This discrepancy in yields likely arises from multiple sources. It could be optimistic yield assumptions, exclusion of network wide scheduling inefficiencies, or simply not sufficiently accounting for all costs. While the model's simplified cost structure and focus on high yield routes may justify elevated margins in early adoption scenarios, the gap signals a risk of overestimating financial viability.

Looking at the income from another perspective, the average revenue per passenger, which serves as a proxy for the mean ticket price, ranges from €100–121. Considering an average flight distance of 409–421 km, these ticket prices are competitive and plausible for short-haul intra-European travel.

Concluding, the overly high yield assumptions inflate projected revenue, potentially overstating the commercial case for electric aircraft. However, the overly high operating cost per ask as seen in Table 24 compensates for the high revenue. While many experiments focus on comparisons and are thus better isolated against such overestimation, the general model outputs are likely optimistic and should be interpreted as upper bound scenarios.

Table 25. Profitability metrics for major European airlines in 2024, with model projections for electric aircraft operations.

Company	Fleet Size	Revenue /Month (M€)	Profit /Month (M€)	Profit Margin (%)	Revenue /Aircraft /Month (k€)	Profit /Aircraft /Month (k€)	Source
Lufthansa	735	3132	115	3.67	4261	156	[97]
IAG	601	2675	228	8.52	4454	379	[98]
AF KLM	574	2622	41	1.56	4564	71	[99]
Ryanair	609	1120	160	14.29	1839	262	[100]
EasyJet	293	656	32	4.88	1889	91	[101]
Finnair	80	254	13	5.12	3180	168	[102]
ERJ 175	100	135.5	63.0	46.0	1354	629	*Model June 2024*
E9X 440	100	146.3	63.4	42.1	1463	634	*Model June 2024*

Kerosene Share of Operating Cost Validation

Fuel cost representation is critical when assessing the economic advantage of electric propulsion. The model's kerosene cost share is validated against two industry benchmarks.

Eurocontrol (2019) reported kerosene at 24.1% of total airline costs and 41% of flight related costs [82]. IATA (2022) estimated fuel and oil at 28.7% globally and 31% in Europe [103]. The model computes a mean kerosene share of 27.7% across variable operating costs (range: 24.9–30.9%) and 21.4% when including fixed costs closely aligned with both references.

The model, therefore, captures the kerosene cost burden with sufficient accuracy.

Routes Validation

Finally, the structural realism of the optimized network is assessed by comparing model outputs to KLM Cityhopper, a leading European regional operator with 65 ERJ 175 aircraft serving 69 destinations[62].

When constrained to a fleet of 65 aircraft and a 10% maximum market share per route, the model serves 33 airports and generates 138 directional legs (69 unique airport pairs). With direct flight only constraints, it serves 28 airports, reducing market share to 5% increases coverage to 29. While exact airport sets differ, the network scale measured in unique connections per aircraft is comparable to real-world operations.

Concluding, the model reliably replicates the operational scope of a regional airline, confirming its ability to generate plausible route structures.

Part II

Literature Study
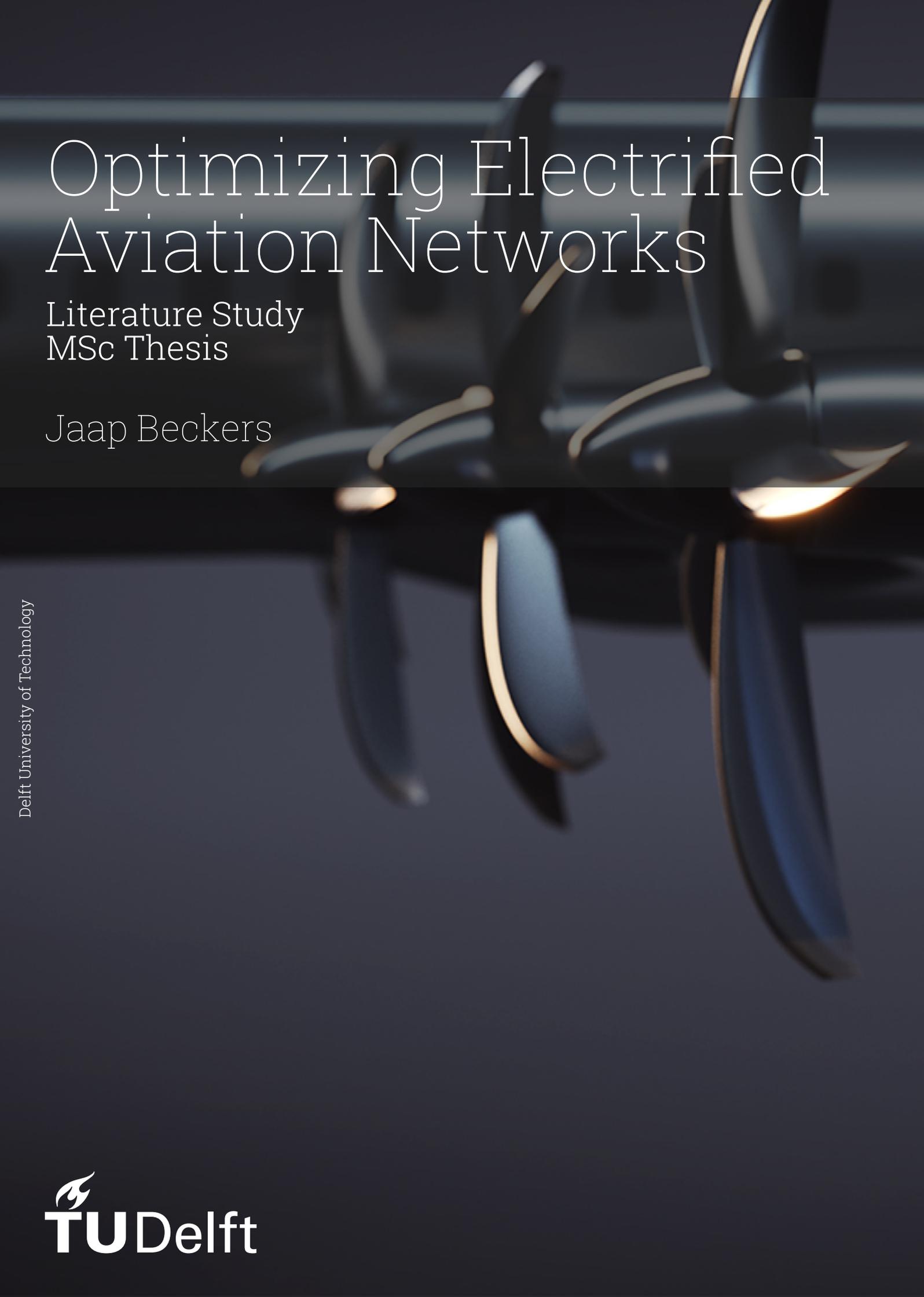
Optimizing Electrified Aviation Networks

Literature Study
MSc Thesis

Jaap Beckers

Delft University of Technology

TUDelft

Optimizing Electrified Aviation Networks: Strategic Planning Under Spatiotemporal Electricity Price Dynamics

Literature Study
MSc Thesis

by

Jaap Beckers

to obtain the degree of Master of Science
at the Delft University of Technology
to be defended publicly on December 10th at 13:00

TUDelft

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
3DFSFA	Three-dimensional Flight Scheduling and Fleet Assignment
AEA	All-Electric Aircraft
AEO	All Engines Operative
ARES	Airport Recharging Equipment Sizing
ASM	Available Seat Mile
Avgas	Aviation Gasoline
BESS	Battery Energy Storage System
BSS	Battery Swaps System
BSS-OF	Battery Swaps System Off-Peak
BSS-ON	Battery Swaps System On-Peak
CCCV	Constant Current - Constant Voltage (Charging)
CP	Constraint Programming
CV	Constant Voltage (Charging)
CVaR	Conditional Value at Risk
DEP	Distributed Electric Propulsion
DNL	Day-Night Average Sound Level
DOC	Depth of Charge
DP	Dynamic Programming
EA	Electric Aircraft
EACN-REG	Electric Aircraft Charging Network for Regional Routes
eARP	electric Aircraft Routing Problem
EASA	European Union Aviation Safety Agency
EDTO	Extended Diversion Time Operations
EIA	Energy Information Administration (U.S.)
EU	European Union
EV	Electric Vehicle
E-VRPTW	Electric Vehicle Routing Problem with Time Windows
FAA	Federal Aviation Administration (U.S.)
FGEA	First Generation Electric Aircraft
FOB	Free On Board
HEA	Hybrid Electric Aircraft
HVAC	High Voltage Alternating Current
HVDC	High Voltage Direct Current
IA	Industrial User Electricity Consumption Band
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
IEA	International Energy Agency
IEEE	Institute of Electrical and Electronics Engineers
IFAM	Itinerary Fleet Assignment Model
IG	Industrial User Electricity Consumption Band
ILP	Integer Linear Programming
ISA	International Standard Atmosphere
ISO	Intermediate Stop Over

Abbreviation	Definition
KPI	Key Performance Indicator
KS	Kernel Search
LCC	Low-Cost Carrier
Li-ion	Lithium-Ion
MCS	Mobile Charging Station
MEA	More-Electric Aircraft
MILP	Mixed Integer Linear Programming
MPC	Model Predictive Control
OD	Origin-Destination
P2P	Point-to-Point
PICS	Plug-in Charging System
PPS	Purchasing Power Standards
PRASK	Passenger Revenue per Available Seat Kilometer
PRASM	Passenger Revenue per Available Seat Mile
PSO	Public Service Obligation
RAM	Regional Air Mobility
SAA	Sample Average Approximation
SAF	Sustainable Aviation Fuel
SOC	State of Charge
TOU	Time-of-Use
WTI	West Texas Intermediate (Crude Oil Benchmark)
YoY	Year-over-Year

Symbols

Symbol	Definition	Unit
g	Gravitational Acceleration	[m/s^2]
H_E	Hybridization of Energy Storage	[-]
H_P	Hybridization of Propulsion Power	[-]
L/D	Lift-to-Drag Ratio	[-]
R	Range	[km]
V	Velocity	[m/s]
W_{bat}	Weight of Battery	[kg]
W_f	Weight of Fuel	[kg]
W_{OE}	Operating Empty Weight	[kg]
W_{PL}	Payload Weight	[kg]
ϵ_{bat}	Specific Energy of Battery	[Wh/kg]
ϵ_f	Specific Energy of Fuel	[Wh/kg]
η_{AEA}	Total Efficiency (All-Electric Aircraft)	[-]
η_{CONV}	Total Efficiency (Conventional Aircraft)	[-]
η_{em}	Efficiency of Electric Motor	[-]
η_g	Overall Efficiency (Conventional Aircraft, range eq.)	[-]
η_p	Propulsive Efficiency	[-]
ρ	Density (Air density implied)	[kg/m^3]
Φ	Power Split Ratio (Hybrid Aircraft)	[-]
GWh	Gigawatt-hour	[Unit of Energy]
kWh	Kilowatt-hour	[Unit of Energy]
MJ	Megajoule	[Unit of Energy]
MWh	Megawatt-hour	[Unit of Energy]
Wh/kg	Watt-hour per kilogram	[Unit of Specific Energy]

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1

Introduction

Environmental sustainability is a major goal for the aviation sector. Currently, aviation accounts for roughly 2.5 to 3% of global carbon dioxide emissions and drives about 7.2% of global warming due to high-altitude atmospheric effects [1]. Fuel efficiency improvements have steadily contributed to reduced emissions per passenger, with annualized gains of 1.9% between 2009 and 2019 [2]. However, in the same period of time, the annualized passenger demand alone has grown by at least 2.9% annually, showing that improvements in fuel efficiency alone are insufficient [3]. With future annualized growth rates predicted between 3 and 5%, it is essential to find more effective ways to reduce aviation climate emissions [4, 5].

As part of this effort, non-emitting propulsion systems, such as Electric Aircraft (EA), have been identified as a promising way forward [6]. By 2050, such non-emitting aircraft are predicted to be responsible for 13% of emissions abatement in aviation according to the International Air Transport Association (IATA), while the International Energy Agency (IEA) estimates their contribution to aviation energy demand at under 2% [7]. One of the non-emitting propulsion systems expected to play a significant role in the future is battery-electric aircraft, also known as all-electric aircraft (AEA) or simply as electric aircraft (EA). It is important to distinguish this from More-Electric Aircraft (MEA), such as the Boeing 787, which utilize electricity for secondary systems rather than propulsion.

Between 2016 and 2022, more than 300 electric aircraft projects have been started worldwide [8]. Electric aircraft promise substantial benefits, including zero direct emissions and significantly reduced noise profiles, estimated to be between 36% and 65% lower than conventional aircraft [9, 10]. Furthermore, maintenance costs for electric aircraft are projected to be substantially lower, with estimates ranging from 20 to 50% below conventional aircraft due to simpler engine designs [11, 12].

However, Electric Aircraft currently face significant challenges due to low battery energy density, which results in shorter flight ranges and reduced seat capacities, and lower cruising speeds compared to their conventionally powered counterparts [13]. Furthermore, the high operating costs per seat associated with serving short-haul routes using small-capacity aircraft could offset their fuel and maintenance economic advantages. Commuter operators experience costs per available seat kilometer almost four times higher than those of large global airlines, mainly driven by lower per seat efficiency [14].

In summary, there is significant uncertainty about the operations of electric aircraft, especially considering operating costs. As the industry transitions to electric aircraft, electricity costs will replace jet fuel as a major component of operating expenses (about 30% of costs today [15]). Although electricity is generally expected to be cheaper than jet fuel for similar-range missions [16], both fuel and electricity prices fluctuate due to market volatility creating significant financial risks for airlines [17]. Electricity prices vary greatly over time and per location and therefore require careful planning to ensure that cost advantages persist and routes remain profitable[18]. This creates an opportunity to optimize profitability

by aligning flight operations with favorable electricity prices.

This literature study aims to provide an overview of current research relevant to optimizing electric aircraft operations with respect to electricity prices. To provide a clear overview, the research field has been broken down into the three most important components, as visualized in Figure 1.1.This diagram serves as a roadmap for the structure of this literature review, defining the distinct fields and their intersection which this research aims to address.
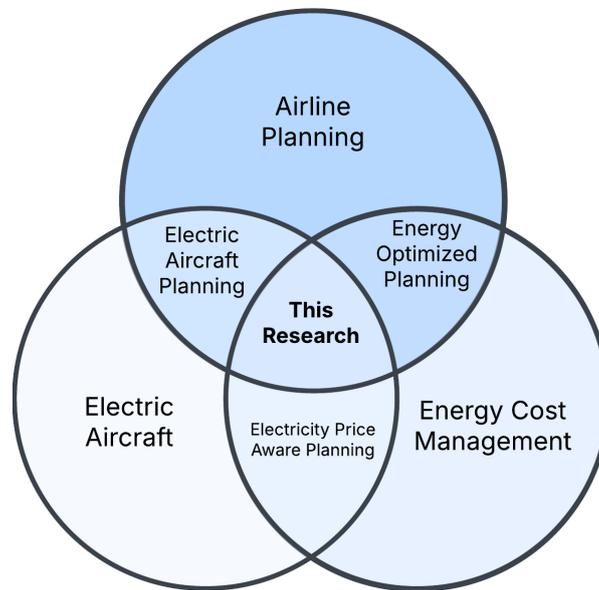
Figure 1.1: Venn diagram showing the three research fields

This research aims to operate within the relatively unexplored intersection of these three fields. By integrating key elements from each area, it seeks to research a gap that has yet to be addressed by the scientific community. The following chapters will provide an overview of the fundamentals of each field, review existing work, and ultimately identify the research gap this study aims to fill.

This literature study is structured to align with the sections and overlaps of the Venn diagram (Figure 1.1). The research begins with Electric Aircraft (chapter 2), the core focus of this study, followed by Energy Cost Management (chapter 3) independently, and then their intersection in Energy Cost Management and Electric Aircraft (chapter 4). Subsequently, airline planning topics are addressed sequentially: conventional Airline Planning (chapter 5), Airline Planning for Electric Aircraft (chapter 6), and Airline Planning focused on Energy Cost Management (chapter 7). These are grouped together as they build progressively, enhancing readability. Next, the integration of all three research areas is explored, highlighting the research gap (chapter 8). Finally, building on this gap, the research proposal and project plan are presented (chapter 9).

<div style="text-align: right; font-size: 3em;">2</div>

Electric Aircraft

Electric aircraft will transform aviation by replacing fossil fuel-powered flight with sustainable alternatives. This chapter examines their potential and challenges. It also presents the E9X aircraft by Elysian, a partner in this research. The E9X is a 90-passenger aircraft with a range of 800–1000 km, expected to enter service by 2033. The chapter covers AEA types, benefits, limitations, history, current projects, and range calculation methods.

2.1. Types of Electric Aircraft

Aircraft can be classified according to the hybridization of their sources of propulsion power (H_P) and energy storage (H_E). Brelje et al. outline five categories of aircraft based on this framework, providing a detailed analysis of each [19]. These categories are summarized in Table 2.1.

Table 2.1: Classification of electric propulsion architectures [19]

Architecture	H_P	H_E
Conventional	0	0
All-Electric	1	1
Turboelectric	> 0	0
Series Hybrid	1	< 1
Parallel Hybrid	< 1	< 1

As clarification, some research refers to MEA which refers to the electrification of secondary aircraft systems in traditionally powered aircraft which represents a different area and should not be confused with the above mentioned aircraft types [20].

This research is being carried out in partnership with Elysian Aerospace. Elysian Aerospace is an aerospace company based in the Netherlands that aims to launch a fully electric aircraft by 2033 called the E9X. The E9X pushes the boundaries of the status quo by aiming to offer a range of 800-1000 km with 90 passengers [21]. This represents a much longer range and larger capacity than any current electric aircraft model, as can be seen in the overview of current electric aircraft in Table 2.4. Due to this partnership, this research will focus on all-electric aircraft. The E9X will therefore be at least one of the aircraft used in the case study of the research, along with other AEA and conventionally powered reference aircraft. The technical details of the E9X are listed in Table 2.2.

Table 2.2: Conceptual E9X Technical Specifications [22]

Parameter	Value	Parameter	Value
Number of passengers [-]	90	AEO climb gradient [-]	8%
Mass per passenger [kg]	100	Contingency energy [-]	5%
Range (target) [km]	1000	Diversion range [km]	150
Take-off field length [m]	2000	Diversion Mach number [-]	0.4
Landing distance [m]	2000	Diversion altitude [m]	1800
Approach speed [m/s]	74.6	Loiter time [mins]	30
Cruise Mach number [-]	0.6	Battery charging time [mins]	<45
Cruise altitude [m]	>7000	Wing span at gate [m]	<36

2.2. Advantages of All Electric Aircraft

There are several advantages to AEA that justify its momentum and adoption. This section will elaborate on these advantages. The section will be concluded with a summary of why these advantages are relevant for this research.

- **Economical Refueling**: Electricity is generally expected to be cheaper than jet fuel for similar-range missions [16], although the high volatility of jet fuel prices means that the difference can vary drastically. The normalized energy cost for both is plotted in Figure 2.1 for the United States Northwest and shows how this advantage is not always guaranteed and definitely changes in magnitude.
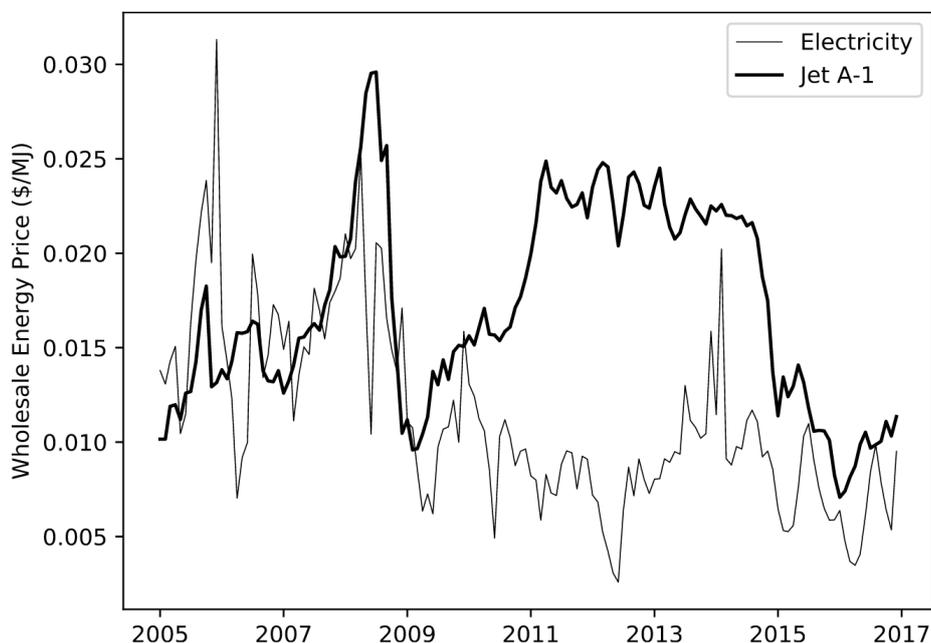
Figure 2.1: Normalized energy cost of Northwest U.S. wholesale electricity versus U.S. Jet A-1 (based on data from the U.S. Energy Information Administration [19, 23, 24]

Very important to note here is that this plot shows energy prices per megajoule (MJ) and does not account for the far higher energy efficiency of electric propulsion systems. Elysian calculated that the E9X will have a total energy efficiency of 77% from generation to propulsion, while the

sustainable aviation fuel (SAF) aircraft are at 13% [21]. The flip side of this is that the added weight of batteries effectively offsets some of this efficiency advantage, as will be discussed in section 2.3. In the research a more accurate plot will be generated that compares jet fuel and electricity prices.

While airports may secure Power Purchase Agreements (PPAs) to stabilize long-term electricity costs (similar to hydrogen production strategies), this research assumes a dependency on spot market pricing. This approach is chosen to analyze the impact of volatility during demand surges or when charging requirements exceed PPA baselines.

The economic viability of electric aircraft depends on the cost difference between electricity and competing oil prices [25]. Investigating how true and cheaper recharging is will be one of the focuses of this research.

- **Possibility for zero operating emissions**:

  All-Electric aircraft do not produce direct emissions during operation. Their effective operating emissions depend on the source of electricity used for charging. Total operating emissions, which include expected emissions from electricity production, general operation, and maintenance, are projected to decrease annual emissions by 93% in a case study of business jets, relative to a comparable conventional aircraft based on the existing energy mix in the studied region [26]. Focusing on green electricity production, Van Amstel explored optimizing AEA flight schedules to align with real-time renewable energy production on a Dutch ABC island case study and found that a 30 minute schedule flexibility could decrease costs by 50% due to the more optimal use of cheaper renewable electricity than grid electricity [27]. The paper did not mention the benefit to emissions from such a flexible schedule, but the paper did maximize the use of green energy.

  Research on the emissions from the construction of all-electric aircraft and their comparison to conventional aircraft is lacking. However, insights from the electric vehicle (EV) industry suggest that electric aircraft production will likely be more emission-intensive due to the large batteries needed. In electric vehicles, battery production accounts for 40 to 60% of total manufacturing emissions [28], Volkswagen reported that electric vehicle production emits 2.5 times more CO_2 than internal combustion engine vehicles [29]. These emissions could be reduced in the future, as Xu et al. project that the emissions from lithium-ion battery cell production could drop from between 41 and 89 kg CO_2-Eq/kWh in 2020 to between 10 and 45 kg CO_2-Eq/kWh by 2050, driven by cleaner electricity for manufacturing and resource extraction [30, 29].

  However, production emissions are extremely minor compared to emissions produced during conventional aircraft operations. Therefore, when powered by renewable energy sources, fully electric aircraft can achieve a substantially lower life-cycle carbon footprint compared to conventional aircraft.

- **Reduced Noise Pollution:**

  Electric aircraft significantly reduce noise compared to conventional engines, cutting community levels by 8 to 20 dB for regional jets and 17 to 29 dB for single-aisle transport aircraft [31]. Despite these gains, aircraft noise remains a persistent challenge. Kish estimated that over 14.2 million people experience at least 55 dB day-night average sound level (DNL) in commercial aviation, with 2.3 million facing significant annoyance [32, 33].

  To address this, regulatory measures are evolving. In April 2023, Schiphol announced a 2026 ban on take-offs from 00:00 to 06:00 and landings from 00:00 to 05:00, effectively reducing operating hours by 20%–25%, though implementation is pending [34, 35]. Furthermore, the European Commission approved a Dutch plan in March 2025 to cut noise exposure near Schiphol by 20% [36]. Although nighttime slots are currently limited [37, 38], electric aircraft, with their lower noise profiles, could allow operations during these hours with minimal disturbance, improving the feasi-

bility in noise-sensitive regions. Despite all this, residual noise may still annoy nearby residents necessitating further research into the operational benefits and impacts of quieter aircraft. Therefore, although the reduced noise profile of electric aircraft is a strength, noise considerations will still need to play a role in future operations.

- **Reduced maintenance requirements:**

Electric motors have fewer moving parts than conventional aircraft engines and thus could offer greater reliability and reduced maintenance costs [39]. Studies estimate maintenance expenses for electric aircraft to be 20 to 50% lower than those of conventional aircraft of comparable size [11, 12]. Additionally, AEA aligns better with More Electric Aircraft technologies which aim to eliminate hydraulics in favor of fully electric secondary systems, which also require less maintenance [12, 40].

- **Shorter Runways and Instant Torque**

Electric aircraft offer superior take-off performance due to instant torque motors that allow operation from shorter runways than conventional aircraft. This characteristic aligns with the profile of Europe's aviation infrastructure, where secondary facilities make up 97% of the available airports but remain underutilized for commercial service [41]. Technologies such as Distributed Electric Propulsion (DEP) systems could even further reduce the take-off distance [42]. It must also be noted that the large weight of batteries could reduce take-off velocity possibly negating the benefits discussed.
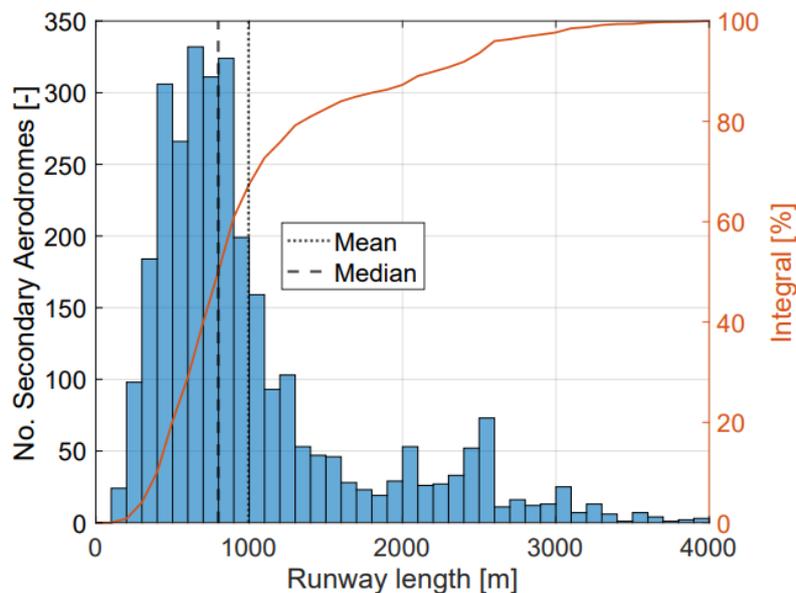
Figure 2.2: Runway length distribution of European secondary aerodromes [41]

Table 2.3: Survey of airports and airfields in Europe [41]

Group	Type	Description	Quantity
Hubs	Hubs	$\geq$ 5M pax/year	69
Secondary aerodromes	Secondary airports	< 5M pax/year	1928
	Airfields	no ICAO code	1101
Total			3098

Figure 2.2 reveals the predominance of shorter runways within Europe. Incorporating all potential airports into network models creates prohibitive computational complexity, while modeling only major hubs fails to capture the value proposition of electric aircraft in serving thin-demand routes from underutilized infrastructure. Salucci et al. addressed this challenge using hierarchical agglomerative clustering with 50km separation thresholds, reducing the node count by 82% while preserving geographic coverage through representative airports for each group [43].

Elysian's E9X has a longer minimum runway length (2000m) than typical electric aircraft because it prioritizes more payload. This specification still enables operation from hundreds of European airports while maintaining commercially viable payload capabilities, serving as a critical filter parameter for airport selection in network optimization modeling.

- **Shorter Runways and Instant Torque**

  Lastly, electric powertrains enable novel aerodynamic layouts that are difficult to achieve with combustion engines, such as Distributed Electric Propulsion (DEP). An example is the six-propeller configuration of the Elysian E9X, which enhances lift and efficiency [21, 44].

Summary of Relevance to This Research

The main advantages of all-electric aircraft are: cheaper refueling, potential for zero operating emissions, lower noise, reduced maintenance, and shorter take-off distances. Understanding these benefits is important as they could be incorporated into the model to improve its accuracy or relevance.

- **Operating Costs**: Will be included in the model by calculating savings from cheaper electricity versus jet fuel, using energy cost data to set pricing parameters. Reduced maintenance costs may be included in the model. Potentially, standard maintenance checks could also be included by forcing aircraft to be inoperative after a certain amount of flight hours or time according to the specifications of their aircraft type. This would allow the reduced maintenance benefit of AEA to have an effect on profitability. However, finding accurate data on maintenance schedules for AEA might be hard.

- **Emissions**: May be included in the model by estimating operating emissions with available electricity mix data, though optimizing for green electricity will likely not be included due to previous work by Van Amstel covering this aspect [27].

- **Noise**: May be included in the model by increasing daily flight limits at airports through operations during noise-restricted hours, adjusting capacity constraints to reflect AEA benefits and potential profit gains.

- **Runway Length**: Will be included in the model by filtering airports based on minimum runway requirements, allowing the addition of smaller aerodromes and expanded route options with various AEA types.

- **Performance Factors**: Will be included in the model by incorporating turn-around times, charging durations, and fuel efficiency as variables to accurately simulate AEA operations.

By adding these elements, the model will test how AEA could perform in future aviation networks.

2.3. Limitations of All Electric Aircraft

However, electric aircraft don't come without their drawbacks and challenges. This section will elaborate on the main drawbacks that could be relevant for this research.

- **Limited Range:**

  One of the primary limitations of AEA is its restricted range, which limits its applicable markets. Epstein et al. reported that in 2019, 92% of global aircraft could not be replaced by AEA due to

insufficient range, due to the limited specific energy (energy divided by weight) of batteries [45]. Currently, electric mobility is predominantly based on lithium-ion (Li-ion) batteries [46]. These batteries offer a favorable balance between cycle life, cost, and energy density [47, 48], yet there remains significant potential for improvement.

Current Li ion batteries provide specific energy of 250 to 350 Wh/kg at the cell level, far below the 12,000 Wh / kg for jet fuel [49, 50, 51, 45]. Note that the energy density of the jet fuel excludes the weight of the fuel tank, while the battery housing is typically included, further highlighting the disparity [52].

To illustrate the effect of different energy densities, jet fuel accounts for 20% to 40% of the Maximum Take-Off Weight (MTOW), while Alice of Eviation, an AEA, has an energy storage mass fraction of 60% at 260 Wh/kg [52]. Also note that at the pack level, practical energy densities drop to 200-260 Wh/kg due to packing efficiency. Although higher values are achievable in lab settings [53, 54].

Driven largely by electric vehicle (EV) development, battery technology has advanced significantly. From 1990 to 2018, patent filings and market size increased steadily [55]. Specific energy has steadily increased by about 5% in the last decade [56], and has grown from approximately 20 Wh/kg in 1950 to almost 300 Wh / kg in 2020, with significant progress made since 2000 [53]. Future projections suggest near-term gains of 400-500 Wh / kg, and within 10-20 years, emerging technologies such as Li-S or Li-air could yield 1,000 Wh/kg [52]. This would significantly expand AEA route and capacity potential.

Figure 2.3 illustrates the specific energy requirements for different aircraft types, underscoring the gap between current capabilities and needs of larger, longer-range aircraft.
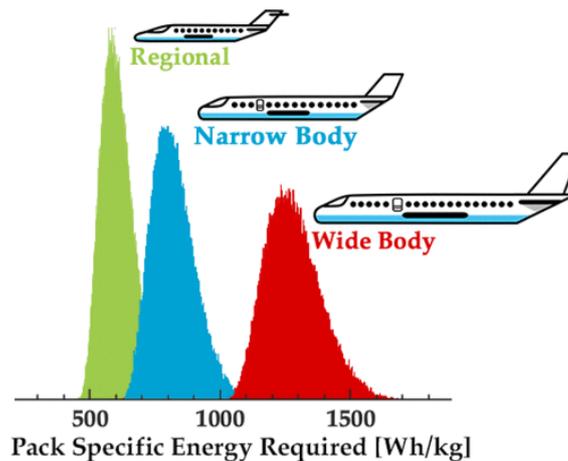
Figure 2.3: Histograms of specific energy for regional, narrow-body, and wide-body aircraft [57].

The research community has also adopted higher specific energies in its research. The review by Sahoo et al. of current AEA research reveals that many studies assume higher battery densities, although projections vary widely, as shown in Figure 2.4 [42].

Battery Energy Density used in current AEA research
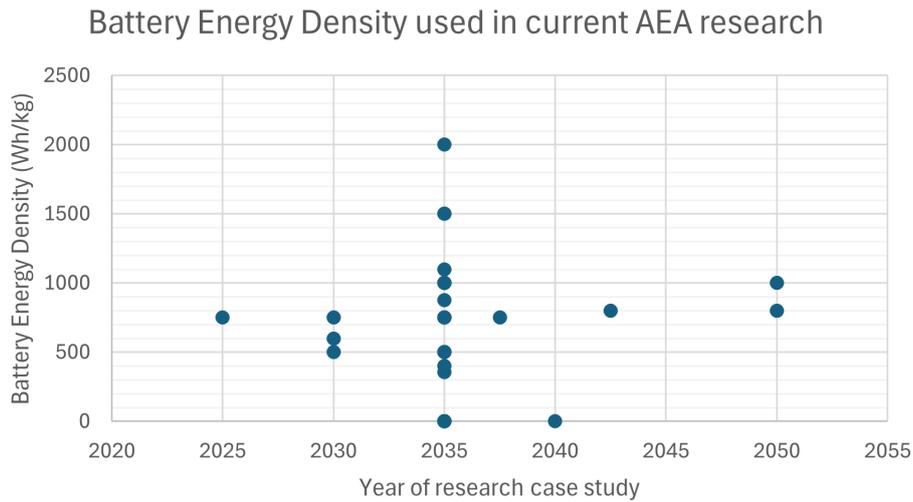
Figure 2.4: Plot of energy densities in current AEA research and their anticipated implementation years.
(own work based on data from Sahoot et al. [42])

Work by de Vries et al. on regional hybrid electric aircraft derived a range equation to vary the power splits (Φ) between conventional and electric propulsion, revealing in Figure 2.5 that beyond a specific battery energy of 500 Wh / kg, the range increases with greater electric dependence. Although the energy density of kerosene (11,900 Wh / kg) is vastly greater than that of batteries, the superior efficiency of electric powertrains ($\eta_{AEA} = 0.95$ vs. $\eta_{CONV.} = 0.35$ [58]) drives this change in the case of small regional aircraft, compensating for the weight penalty as the energy density of the battery improves.
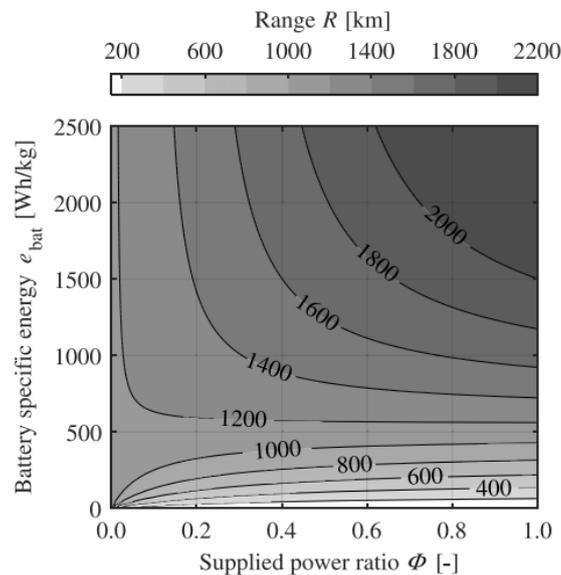
Figure 2.5: Aircraft range as a function of supplied power ratio and battery specific energy [58]

The future could also be bright without significant increases in battery energy density. Recent work by Wolleswinkel et al. suggests that optimized battery electric aircraft, using improved energy mass fractions and aerodynamic efficiency, could achieve greater ranges than previously estimated, potentially allowing viable commercial use even at current densities around 300 Wh/kg [59].

Finally, Vehlhaber et al. emphasized the importance of sizing the battery to match the mission profile. In their case study of the Dutch ABC islands, they determined that significant costs (17.31%) arose from an oversized battery, which increased power demands for short missions [60].

- **Constant Battery Weight:**

Unlike conventional fuel, which becomes lighter as it is consumed, batteries maintain their mass throughout flight, eliminating the beneficial weight reduction effect that improves aircraft range in fuel-powered aircraft [42]. This fundamental difference is reflected in the fundamental range equations for conventional and electric aircraft [58]:

$$R = \eta_{\text{gl}}\eta_{\text{p}} \left(\frac{L}{D} \right) \left(\frac{e_{\text{f}}}{g} \right) \left(\ln \left(\frac{W_{\text{OE}} + W_{\text{PL}} + W_{\text{f}}}{W_{\text{OE}} + W_{\text{PL}}} \right) \right) \tag{2.1}$$

$$R = \eta_{\text{em}}\eta_{\text{p}} \left(\frac{L}{D} \right) \left(\frac{e_{\text{bat}}}{g} \right) \left(\frac{W_{\text{bat}}}{W_{\text{OE}} + W_{\text{PL}} + W_{\text{bat}}} \right) \tag{2.2}$$

Equation 2.1 represents the conventional Breguet range equation for fuel-powered aircraft, showing a logarithmic dependency on weight due to its reduction throughout flight. In contrast, Equation 2.2 for fully electric aircraft shows a linear relationship, as battery weight remains constant. This mathematical difference illustrates a significant challenge for electric aviation.

- **Battery Lifecycle Challenges:**

The battery life, and consequently the range, of electric aircraft degrades over usage cycles and time, requiring frequent replacement or reassignment to shorter routes. Battery life is typically defined as the duration until the capacity reaches 80% of its initial value [61]. Cells degrade due to calendar aging, cycle aging, environmental factors, and irreversible physical-chemical changes [62]. Current lithium-ion technology offers only 1,000 to 2,000 cycles before significant capacity loss occurs [63, 64]. In Electric Aircraft, this could easily require yearly replacement, even with 3,500 deep discharge cycles for single-aisle aircraft, due to high utilization [45]. Clarke and Alonso's modeling showed that continuous high-utilization operation for one year could reduce capacity by 45% in urban air mobility scenarios [62].

Degradation is also dependent on the Depth of Charge (DOC) and the specific State of Charge (SOC), also known as the battery level. If the battery is charged starting with an SOC around mid-level, the battery is likely to degrade less [27, 65, 66].

Degradation varies with operational profiles, as higher velocities increase drag and current demands [67]. Figure 2.6 illustrates that cumulative lifetime endurance is highly sensitive to cruise velocity and maximizes at the optimal cruise speed.
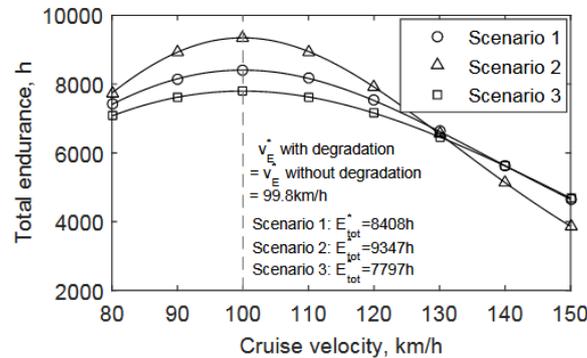
Figure 2.6: Total endurance of electric aircraft over cruise speed [67]

Future technologies could extend the cycle life to 5,000 to 7,500 cycles [61], while advanced lithium titanate batteries can achieve 15,000 to 20,000 cycles before dropping below 80% capacity [68]. Despite its significant long-term impact, many electric aircraft studies omit battery degradation considerations, leaving them for future work to address [69, 70].

- **Reduced Operating Speed:**

Electric aircraft use slower propellers instead of turbofans, achieving speeds similar to those of turboprop aircraft. Optimal cruise speed may decrease further on longer routes to maximize range dependent on the optimal cruise speed. Baumeister et al. found that First Generation Electric Aircraft (FGEA) flights would take 10 minutes longer than comparable Cessna jets on 250km routes and 20 minutes longer on 500km routes [71]. Future passengers might accept these delays based on environmental benefits, also referred to as the *green factor* [25].

- **Slower Turn-around Times:**

Electric aircraft are expected to initially serve short-haul markets, typically under three hours of flight time, where high aircraft utilization and efficient turnarounds are critical for airline business models [72, 73]. However, recharging EA introduces slower turnaround times compared to traditional actions like deboarding, reducing utilization—the ratio of operating time to ground time. This poses a challenge, particularly for short-haul operations where rapid turnarounds are essential for profitability. Research indicates that efficient turnaround processes are vital for maintaining high utilization rates, a factor that EA must address to compete effectively in these markets [72].

Recharging methods for EA primarily include plug-in charging and battery swapping, each with distinct time implications. Battery swaps are estimated to take approximately 30 minutes [70], while the duration of plug-in charging varies according to battery state of charge, ambient conditions, and battery C rating. A 1C-rated battery charges in one hour, a 2C in 30 minutes and a 5C in 12 minutes, with automotive targets reaching 10C for a 5-minute charge to 80–90% capacity [74]. Charging power also affects time, as demonstrated by Westin et al. (2024), who found that fast charging infrastructure (30 vs. 90 minutes) reduced fleet requirements by 40%, increased utilization from 22.7% to 23.2%, and cut costs by 31% [75]. There also exist different methods for managing current and voltage during plug-in charging, such as Boostcharging.

Boostcharging, proposed by Notten et al., applies an initial high-voltage Constant Voltage (CV) phase to rapidly charge Li-ion cells before transitioning to Constant Current - Constant Voltage (CCCV) [76]. This leverages low impedance at low states of charge to enable high currents without immediate degradation. However, concerns over long-term electrode stress, electrolyte breakdown, and safety risks have hindered its adoption. The paper is also from 2004 but is not widely used yet, implying that this method is hard to implement or has other drawbacks.

Charging strategies further complicate turnaround times due to battery health considerations. Fast charging above 80% state of charge (SOC) is discouraged for safety, affecting charging station optimization [27]. Slow charging, while optimal for extending battery cycle life, requires several hours, rendering it impractical for commercial operations except for overnight charges [74]. This creates a trade-off between battery longevity which leads to maintenance downtime and replacement costs, and operational demands for quick turnarounds. However, a 2016 study by Xu et al. found that a 0.5C charging rate caused more mechanical damage than a 2C charging rate showing that there might be some room for healthy fast charging [77].

Future aircraft will likely employ partial charging, where aircraft are charged only to the level required for the next mission, reducing ground time as explored in flight scheduling studies by Pereira [78]. A possible reason not to partially charge is to ferry over cheaper electricity to use for the next mission.

Charging is often modeled using a linear or bilinear charge curve instead of a more complex curve to limit the model complexity. The difference between the two is shown in Figure 2.7.
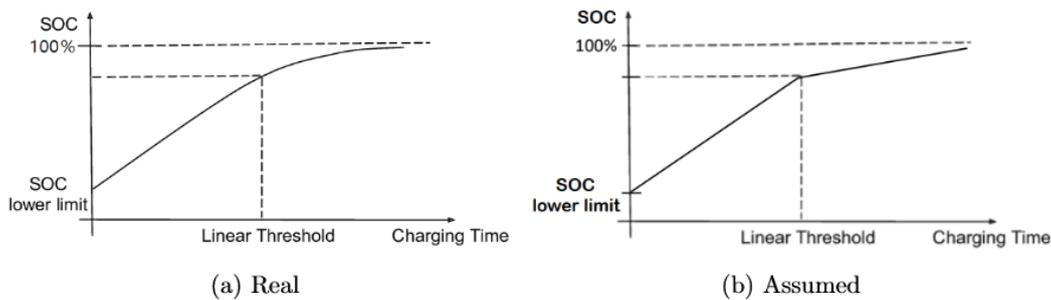
Figure 2.7: Charging profile of Lithium-Ion batteries [78]

Slower turnarounds also affect airport operations, particularly at congested facilities with limited stand capacity. Extended ground times can reduce overall airport capacity and disrupt the servicing of arriving aircraft [79]. This is critical for busy airports where stand availability directly influences throughput. The ability to turnaround EA within a timeframe acceptable to both airlines and airport operators is thus a key factor in their adoption [74]. Innovations in charging infrastructure and scheduling will be necessary to mitigate these knock-on effects and maintain operational efficiency.

In conclusion, the integration of electric aircraft into short-haul markets hinges on overcoming slower turnaround times driven by recharging needs. While battery swapping and fast-charging infrastructure offer potential solutions, they must balance operational efficiency with battery health and safety constraints. Airport congestion further complicates deployment, emphasizing the need for optimized charging strategies and infrastructure investments. Addressing these challenges will determine the commercial viability and widespread adoption of EA, aligning technological capabilities with the demands of high-utilization airline operations.

- **Charging Infrastructure Requirements:**

The adoption of Electric Aircraft requires significant investment in airport charging infrastructure that is capable of rapidly recharging batteries between flights. This presents unique technical challenges, including the development of megawatt-level charging systems and high-rate-capable batteries that maintain safety and longevity. Doctor et al. highlight the challenges in the requirements of utilities in terms of electricity demand, and the challenges of retrofitting legacy airports with widespread electric charging capabilities [74]. According to Epstein and O'Flarity (2019), if all commercial aviation were electrified, the world would need to increase electricity production by 26% [71]. A more in-depth study of infrastructure requirements is conducted in section 6.2.

- **New technology adoption:**

The slow public adoption of electric aircraft could also slow down its development. A market perception study highlighted several concerns, including the risk of battery explosions, long charging times, performance changes in low temperatures, and limited battery lifespan. However, the same study also identified key opportunities, such as lower fuel costs and reduced regulatory pressure related to carbon emissions [16].

- **Increasing Electricity Price Dynamics:**

The charging demand of electric aircraft could significantly increase the electricity needs of airports. This substantial power demand could potentially drive electricity prices upward if supply expansion fails to match consumption growth. Schaefer et al. estimated that a global fleet of all-electric aircraft serving routes up to 400 to 600nm would require approximately 0.6 to 1.7% of 2015's global electricity consumption [9]. Short-term hourly price increases could also be induced by concentrations of EA charging during peak airport operational hours due to sudden demand surges, although Battery Energy Storage Systems (BESS) offer promising mitigation strategies for these temporal demand spikes. While the feedback loop of airline demand influencing grid

prices is a critical factor, explicitly modeling grid demand response is considered out of scope for this specific study.

Summary of Relevance to This Research

The main limitations of AEA are limited range, constant battery weight, battery lifecycle challenges, thermal management complexity, reduced operating speed, slower turn-around times, charging infrastructure requirements, new technology adoption, and increasing electricity price dynamics. These affect operational feasibility and are assessed for model inclusion below.

- **Limited Range**: Will be included by capping available route which will be defining for network design and profitability.

- **Constant Battery Weight**: Will be included via fixed battery mass in range calculations, reducing efficiency and payload compared to fuel-based aircraft.

- **Battery Lifecycle Challenges**: May be included by modeling degradation (1,000–2,000 cycles) and its impact on range and maintenance, if data is available.

- **Reduced Operating Speed**: Will be included by adjusting flight times, thereby cutting daily flight frequency and utilization.

- **Slower Turn-around Times**: Will be included with charging times in ground time estimates, affecting utilization and airport capacity. Bi-linear charging could also be included into the model to more accurately reflect real charging rates.

- **Charging Infrastructure Requirements**: May be included as cost and capacity constraints.

- **New Technology Adoption**: May be included as a demand factor reflecting public perception.

- **Increasing Electricity Price Dynamics**: May be included by varying costs with demand surges.

2.4. Evolution of Electric Propulsion in Aviation

This section will provide an in-depth look at the history of Electric Aircraft in order to put current developments into context. Electric aircraft may seem like a technology of the future, but they have a long history, and understanding their origins provides insight into their recent resurgence. This chronological review highlights key developments that have shaped the field.

- **19th Century Origins:** On October 8, 1883, Gaston Tissandier flew the first electrically powered airship, followed by Charles Renard and Arthur Krebs' more powerful La France airship in 1884, although both were severely limited by heavy accumulators [80]

- **Early Vertical Flight:** In 1917, the Petróczy-Kármán-Žurovec PKZ-1 electric-powered helicopter flew briefly with a 190 hp electric motor powered via cable from a ground generator, though motor limitations led to burnout after minimal flight time [81]

- **First Manned Electric Fixed-Wing:** The Militky MB-E1, piloted by Heino Brditschka on October 21, 1973, became the first manned electric aircraft to fly under its own power, achieving a 15-minute flight using nickel-cadmium batteries [82]

- **Solar Aviation Pioneers:** The Mauro Solar Riser (1979) became the first solar-powered manned aircraft, while the MacCready Solar Challenger (1981) demonstrated practical solar flight by completing a 163-mile cross-Channel journey from France to England [83, 84, 85]

- **NASA's High-Altitude Program:** From 1995-2001, NASA's progression of solar unmanned aircraft (Pathfinder, Pathfinder Plus, and Helios) set altitude records, with Helios reaching 29,524 meters (96,863 ft) and demonstrating long-endurance capabilities [86]

- **Modern Breakthroughs:** Key milestones include the Taurus Electro (2007) as the first two-seat electric aircraft, Solar Impulse 2's global circumnavigation (2016), and the Pipistrel Velis Electro

achieving the first electric aircraft EASA type certification in 2020 [87, 88, 89]. An overview of current electric aircraft is presented in Table 2.4.

Electric aircraft development was slow and received little attention mainly because of the limited battery energy density, making practical electric flight impossible. The recent resurgence is driven by three converging factors:

- Advances in lithium-ion battery technology as discussed in section 2.3
- Growing environmental concerns about aviation emissions as discussed in the introduction.
- The successful adoption of electric vehicles creates technological spillovers [90].

2.5. Current Electric Aircraft

As mentioned in chapter 1, there are hundreds of electric aviation projects in drastically different stages of development. This section will give an overview and list their key specifications.

Table 2.4: List of 10 Electric Aircraft Projects

Aircraft	First Flight	Development Stage	Range (km)	Seats	Source
Elysian E9X	2030*	Development	800-1000	90	[21]
Wright Spirit	2030*	Development	1000	100	[91, 92]
Maeve M80	2028*	Development	1400-2200	76-84	[93, 93]
Heart Aerospace ES-30	2026*	Development	200	30	[94]
RX4E	2024	Production	300	4	[95]
Eviation Alice	2022	Testing	460	11	[96]
Pipistrel Velis Electro	2020	Production	100-200	2	[97]
Beta ALIA CX300 CTOL	2019	Prototype	620	6	[98]
Lilium Jet	2017	Prototype	300	7	[99, 100]
Joby S4	2017	Prototype	240	5	[101, 102]

*Projected/anticipated first flight

2.6. Calculating Electric Aircraft Effective Range and SOC

Lastly, it is important to understand how to calculate the effective range and SOC after a mission for electric aircraft. Determining the effective range of Electric Aircraft requires precise energy calculations that account for multiple factors: the flight profile, safety buffers, and imperfect flight paths. These elements influence both the total effective range and dynamic recharging times, which depend on the SOC post-mission. Pereira's analysis of electric aircraft scheduling, which incorporates battery swapping and charging based on dynamic SOC, uses more accurate calculations of energy consumption based on flight profiles [78] and shows the importance of understanding energy consumption across mission profiles.

2.6.1. Flight Profiles

The simplified range equation for electric aircraft shown in Figure 2.3(Equation 2.2) focuses on the cruising phase, yet this phase constitutes only a fraction of short regional flights, leading to inaccurate energy predictions for small flights[52].

A more detailed approach uses the flight profile, which encompasses the velocity and altitude variations. The flight is then divided into five phases: takeoff, climb, cruise, descent and landing, calculating the energy needs for each based on the mission-specific profile, often derived from Flightradar24 records [52, 103]. Factors such as climb rates, cruising altitudes, and flight distance shape the profile.

Baerheim uses flight profiles to accurately calculate the energy consumption per route [52]. Similarly, Vehlhaber uses Flightradar24 data to model energy use based on realistic flight paths [60, 103]. An

example of flight profiles and how they change per flight is shown in Figure 2.8.
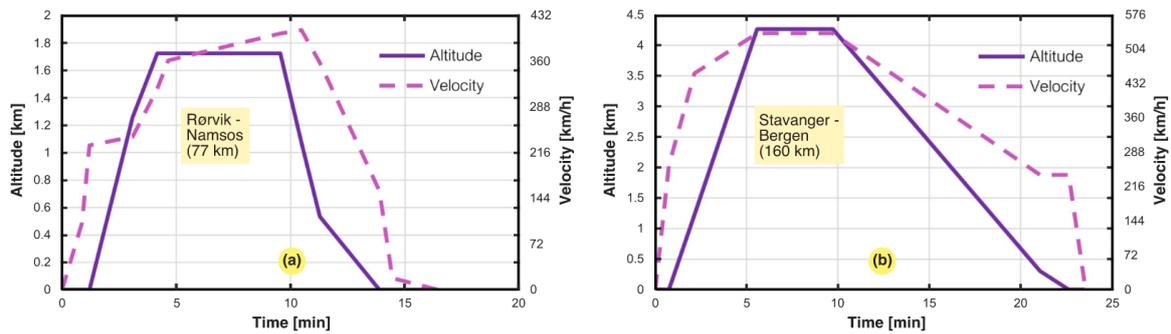
Figure 2.8: Flight profiles for two short-range flights [52].

2.6.2. Safety Buffers

Electric aircraft, like conventional ones, must carry energy reserves to comply with safety regulations. Key requirements include:

- **Unplanned Contingency Fuel**: 5% of trip time (ICAO Annex 6.3.6.3c) or 10% (FAA) [104, 105].

- **Final Reserve Fuel**: 45 minutes of loitering at 1500 ft at holding speed, aligned with reciprocating engine rules [104].

- **Destination Alternate Fuel**: Energy to reach an alternate airport, assuming an Extended Diversion Time Operations (EDTO) classification for EA of 60 minutes (per Annex 6 section 4.3.6.2d, EDTO Doc 10085 [106].). The E9X design adopting a 150 km diversion range. [106].

These buffers also protect battery health by preventing deep discharges. Pereira simplifies this into a single 20% capacity reserve, a practical approximation further explored in subsequent sections [78].

2.6.3. Imperfect Flight Paths

Flight paths deviate from the shortest great circle distance due to weather, airspace restrictions, overfly costs, and EDTO rules. Commercial flights average a 7.6% lengthening globally [107], with greater deviations in restrictive regions like China. Research suggests adjustments of 10% for long-haul and 5% for short-haul flights [108]. These detours must be factored into range calculations to ensure accurate modeling of electric aircraft performance.

This comprehensive approach integrates flight profiles, safety buffers, and path deviations to provide a robust estimate of effective range. This can be utilized in the research model to more accurately calculate the energy consumption of various flights, enabling precise modeling of shorter routes.

<div style="text-align: right; font-size: 3em;">3</div>

Energy Cost Management

Balancing networks with jet fuel prices has long been important for airlines and therefore has received ample research attention as will be elaborated on in chapter 7. However, first, to properly analyze how such a network rebalances when based on electricity prices, a proper understanding of how jet fuel is priced and varies is needed. This chapter will elaborate on jet fuel types, specifics about its price volatility and localization, and finally explain how airlines manage jet fuel price risk through hedging techniques.

3.1. Types of Aviation Fuel

Aviation fuels are broadly classified into two primary types based on the propulsion systems they power: jet fuels for turbine and turboprop engines and aviation gasoline (Avgas) for piston-engine propeller aircraft. Jet fuels, which are kerosene-based, include Jet A, predominantly used in the United States, and Jet A-1, the international standard [109]. The key distinction between these two lies in their freezing points: Jet A-1 has a lower freezing point making it more suitable for colder climates and high-altitude operations. These fuels power most commercial aircraft, including jets and turboprops, which dominate short to medium-haul routes.

A third category, Sustainable Aviation Fuel (SAF), has emerged as an alternative to conventional jet fuels. SAF is produced from nonfossil feedstocks such as used cooking oil, plant oils, municipal waste, waste gases, and agricultural residues. It is designed as a "drop-in" fuel, meaning that it can be blended with conventional jet fuel (currently limited to a 50% blend by ASTM D7566 regulations [110, 111]) and used in existing aircraft engines without modification [112, 113]. SAF aims to reduce lifecycle carbon emissions by up to 80% compared to traditional jet fuel [111]. However its adoption remains limitied. In 2024, SAF accounted for less than 0.2% of global aviation fuel consumption, although projections suggest that it could reach 0.6% by 2025, adding approximately 3.8 billion USD to airline fuel costs due to its high price of $2,500 per tonne, more than three times the cost of conventional jet fuel at USD 800 per tonne [114].

In contrast, piston-engine propeller aircraft rely on aviation gasoline (Avgas), a leaded fuel distinct from unleaded motor gasoline because of the inclusion of tetraethyl lead. This additive improves octane ratings and provides lubrication for piston engines, which are typically found in smaller general aviation aircraft rather than commercial fleets [115]. Efforts to phase out toxic lead from Avgas are ongoing, driven by environmental and health concerns.

3.1.1. Selecting a Fuel for Comparison with Electricity Prices

To evaluate the economic effectiveness of electric aircraft, it is necessary to select an appropriate aviation fuel benchmark. Avgas, used in piston-engine aircraft, might seem intuitive since current electric aircraft use electrically driven propellers. The capacity (90) and range (800-1000 km) of E9X aircraft

cannot be matched by comparable propeller aircraft and would require turboprop or turbofan aircraft, and almost all commercial traffic relies on turboprop or turbines, while piston driven propellers, used in a small fraction of commercial aviation, serve primarily general aviation and special missions such as bush planes rather than scheduled passenger services [116]. One reason for this research to also consider Avgas would be for small-capacity electric aircraft with very small ranges, as these could realistically be operated by piston-driven propeller aircraft.

3.2. Volatility of Jet Fuel

Jet fuel prices can be very volatile, with prices changing by a couple of percentages every week, as can be seen in Figure 3.1. Unlike electricity, they do not change per hour of the day. Changes in jet fuel prices are tracked by multiple organizations, including the IATA which provides weekly publicly available updates as shown in Figure 3.1. It also shows that the maximum price difference between regions is about 7%, which is much lower than the differences in electricity prices, as will be discussed in section 3.3 and Figure 4.1.

Fuel Price Analysis

The global average jet fuel price last week rose 2.3% compared to the week before to $88.68/bbl.

Week ending 21 Mar 2025	Share in Global Index	Weekly Average Price			Index Value (Year 2000 = 100)	Weekly Average Price versus		
		cts/gal	$/bbl	$/t		prior week's average	prior month's average	prior year's average
Jet fuel price	100%	211.14	88.68	700.30	242.4	2.3%	-6.2%	-10.5%
Asia & Oceania	22%	203.20	85.35	674.21	243.8	0.8%	-7.2%	-11.0%
Europe & CIS	28%	213.23	89.56	706.60	241.3	1.3%	-5.1%	-10.8%
Middle East	5%	195.85	82.26	649.82	245.6	0.5%	-7.6%	-13.7%
North America	39%	215.52	90.52	715.08	240.6	4.0%	-6.4%	-9.5%
Latin & Central America	4%	217.46	91.33	721.52	253.0	3.0%	-6.7%	-11.8%
Africa*	2%	211.22	88.71	700.26	87.8	1.2%	-5.2%	-12.2%
Oil Price (Dated Brent)			72.12			0.9%	-4.0%	-10.7%
Crack Spread			16.56			9.0%	-14.8%	-9.5%

*The Africa index was launched on 2 January 2025, carved out from the Middle East and Africa index. Because of its newness, its values are indexed to its 2024 annual average value, unlike the other regional indices, which are indexed to their respective average annual values in 2000.

Figure 3.1: Jet fuel price Monitor for 21/03/2025 [117]

Jet fuel prices are heavily dependent on crude oil, which serves as the primary ingredient. The difference between these two prices, known as the crack spread, is typically stable. However, during periods of volatility, the spread can widen significantly, as illustrated in Figure 4.3. When this happens, jet fuel prices often increase more sharply than crude oil prices. For example, the invasion of Ukraine in 2022 contributed to lower crude oil and refined product exports, especially to Europe, and thus triggered global volatility and expanded crack spread [118]. As a result, daily jet fuel prices diverged noticeably from crude oil prices, as shown in Figure 3.2.

Daily jet fuel vs. daily crude oil prices (nominal)

US Gulf Coast kerosene-type jet fuel spot price FOB
Dollars per gallon, January 4, 2021–June 27, 2022
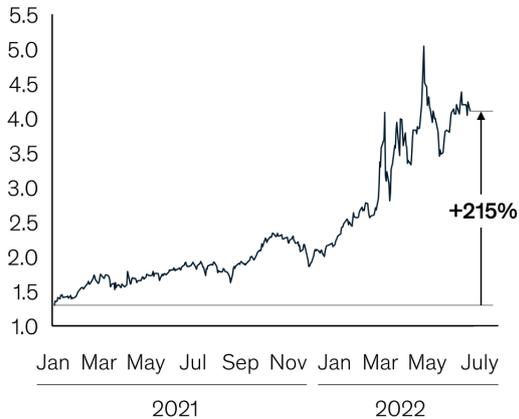
Crude Oil: West Texas Intermediate (WTI)
Dollars per Barrel, January 4, 2021–June 27, 2022

Source: US Energy Information Administration (EIA), Federal Reserve Economic Data (FRED)

Figure 3.2: Daily jet fuel vs. daily crude oil prices (nominal) [118]

Jet fuel prices respond to factors beyond just crude oil prices. IATA mentioned that the 2024 drop in jet fuel prices is partially caused by the decreased demand for diesel [114]. As both diesel and jet fuel are produced in any refinery, the drop in demand for the former benefits the latter. In addition, environmental regulations and regional demand surges can lead to sudden market spikes. Supply disruptions and geopolitical events, such as those caused by natural disasters or military conflicts, further drive fluctuations [119]. In general, jet fuel remains highly vulnerable to these disruptions.

Lastly, the research on jet fuel pricing does not use any metric to measure volatility. Several options are available, including historical volatility, implied volatility, and the average true range. This research could apply one or more of these metrics and connect price volatility to other model outputs.

3.3. Locality of Jet fuel prices

Jet fuel is a globally traded commodity, which reduces the influence of local factors on its price. This global dependency is visualized in Figure 3.3, which illustrates the net trade balance for the EU-27. In this chart, bars extending to the left (negative values) indicate net imports, revealing that the vast majority of the EU's jet fuel deficit is covered by imports from the Middle East (Light Green) and Asia Pacific (Dark Blue)—accounting for 91% of imports in 2022. The category labeled 'Net Exports Non EU' (Light Blue) functions as an aggregate for other non-EU regions. This heavy reliance on distant markets contrasts sharply with electricity prices, which tend to spill over to neighboring countries but rarely extend much further [120]. Consequently, jet fuel prices in Europe are driven by global market dynamics rather than local production.
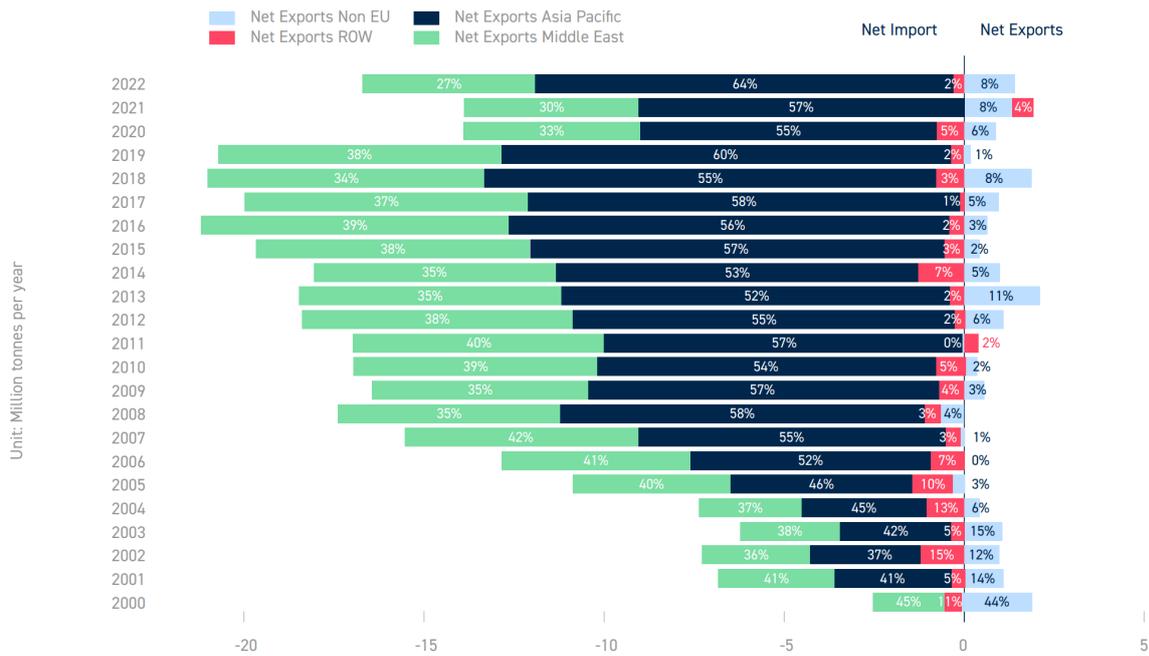
Figure 3.3: EU-27 Jet fuel trade balance [121]

Consolidated reports on jet fuel prices in Europe remain scarce despite the availability of raw data, which will require processing for use in this research. For the purposes of this study of the literature, related oil derivatives such as gasoline and diesel offer a proxy for understanding the volatility of jet fuel prices. The prices of jet fuel are closely aligned with ultra-low sulfur diesel, a product whose price serves as a frequent reference for jet fuel supply contracts due to their high correlation [122].

Figure 3.4 depicts the location of the diesel price in the EU as of March 2025 showing that there are differences between countries. However, this map can be misleading since diesel prices include drastically different national taxes. In contrast, jet fuel for intra-EU flights remains untaxed under EU regulations [123], resulting in less localized and more uniform pricing between countries.

Diesel, EUR per 1000 litre
17/03/2025

Administrative boundaries: © EuroGeographics © UN–FAO © Turkstat
Cartography: Eurostat – IMAGE, 03/2025
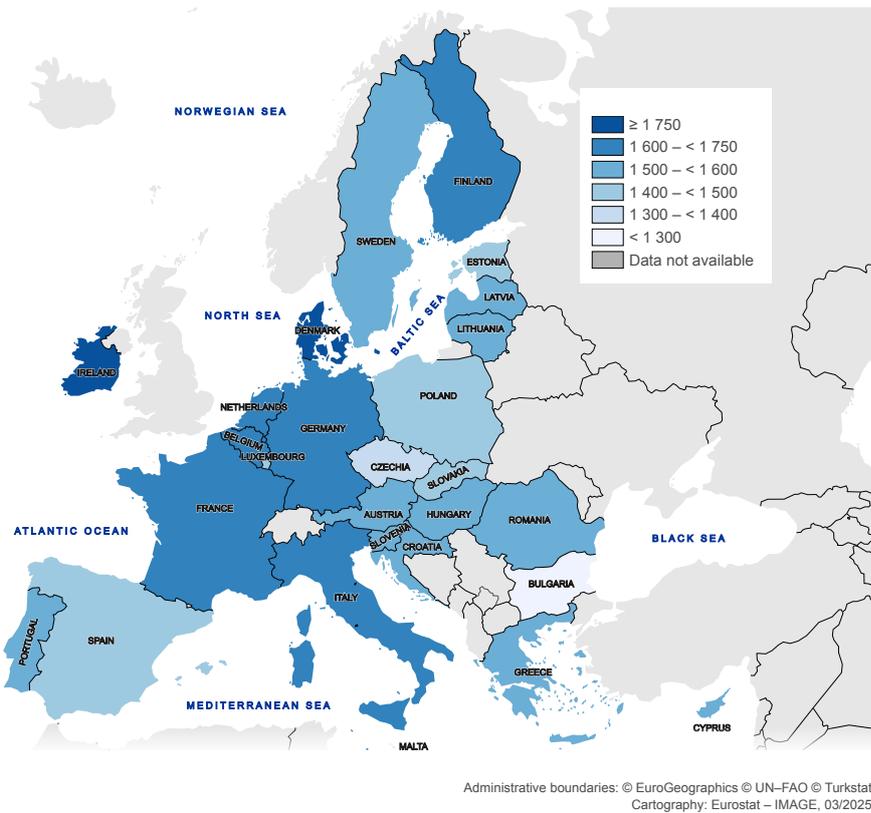
Figure 3.4: EU diesel prices by Eurostat (20/03/2025) [124]

This exploration of jet fuel prices in Europe reveals a clear need for more refined research. The construction of a comprehensive database of historical jet fuel prices per country is likely to prove essential to advance this study. Such a database could be developed by consolidating various publicly available datasets, providing a robust foundation for further analysis.

3.4. Fuel Hedging

Airlines can reduce the impact of unpredictable jet fuel prices by using financial hedging tools to set future purchase prices. With contracts like futures or forward contracts, an airline can lock in a fixed price for a specific amount of jet fuel over a certain time, protecting itself from price increases but missing out on potential price decreases [125]. These simple derivatives, which are agreements to buy or sell an asset at a set price and time, help minimize price swings and manage risk effectively. Another option is to use options, which give the airline the right, but not the obligation, to act, although they come with a cost, unlike forward contracts and futures, which are free to start [125]. Most airlines hedge between six months and one year in advance [126]. However, many airlines face a challenge because their financial departments handle the hedging separately from operational planning, often resulting in less than ideal results compared to a fully coordinated approach [125].

Hedging offers clear advantages, such as cost certainty and protection from price volatility. For example, in 2022, European airlines such as IAG, Lufthansa and Ryanair gained 5 billion euros in mark-to-market value from fuel hedges, securing prices between $73 and $100.8 per barrel, while jet fuel prices jumped to $139 per barrel after Russia's invasion of Ukraine [127]. On the downside, overhedging can be a problem during unexpected downturns. In 2020, European airlines lost $4.66 billion when Covid-19 cut

demand, leaving them stuck with hedges for fuel they did not need as oil prices fell [128]. Over the long term, hedging should balance out to about a zero net value, minus an acceptable fee for the provider. This dual nature of hedging shows up in the different strategies that airlines use and how much of their future fuel use they choose to hedge, as shown in Figure 3.5.

Airlines	Time period covered	Hedged every year?	Merger & reporting
American Airlines	2000–2012	Yes	
Continental Airlines	2000–2009	No	Acquired by United in 2010.
Delta Airlines	2000–2007	No	Acquired Northwest in 2008.
Delta Airlines (post-merger with Northwest)	2008–2012	Yes	Combined reporting after October 29, 2008.
Northwest Airlines	2000–2008	No	Acquired by Delta in 2008.
United Airlines	2000–2009	No	Acquired Continental in 2010.
United Continental	2010–2012	Yes	Combined reporting after October 2010.
US Airways	2000–2004	No	Acquired by America West in 2005
US Airways (America West post-merger)	2006–2012	No	America West-US Airways combined reporting began in 2006.
America West	2000–2005	Yes	Acquired US Airways in 2005.
Southwest Airlines	2000–2010	Yes	Acquired Air Tran in 2010.
Southwest Airlines (post-merger)	2011–2012	Yes	Combined reporting after May 2, 2011.
JetBlue	2000–2012	Yes, except 2000[a]	
AirTran	2000–2010	Yes	
Frontier Airlines	2000–2008	No	Acquired by Republic in 2009.
Allegiant	2005–2012	No	
Alaska Air	2000–2012	Yes	
Hawaiian Airlines	2000–2012	Yes	
Great Lakes Airlines	2000–2012	No	
Republic Airways	2004–2008	No	Acquired Frontier. Combined reporting after October 1, 2009.
Republic Airways (post-merger)	2009–2012	Yes	
Skywest Airlines	2000–2012	No	
Spirit Airlines	2010–2012	Yes	

[a] **Note:** Fuel hedging implementation began in 2001.

Figure 3.5: Jet fuel hedging techniques for US based airlines between 2000 and 2012. [129]

3.5. Relevance for this Research

This chapter explored the types of aviation fuel, the volatility of jet fuel price, the locality of the pricing, and the hedging strategies of airlines. These elements are critical to understanding how fuel costs influence airline network design and operational efficiency, providing a foundation for comparing jet fuel dynamics with electricity prices in the context of the adoption of electric aircraft. The key findings and their implications for the research model are described below.

- **Types of Aviation Fuel**:
  Jet A-1 is selected as the benchmark for comparison with electricity prices, reflecting its dominance in European commercial aviation. This choice will anchor the fuel cost input of the model, while the high cost and limited adoption of SAF can be included as a sensitivity factor to assess future scenarios.

- **Volatility and Locality of Jet Fuel Prices**:
  Jet fuel prices are volatile, but lack the hourly variations seen in electricity prices. They also show limited localization due to their nature as a global commodity. This will be incorporated into the model by seeking accurate price data for each country, though challenges in obtaining country-specific data may require extrapolation from available sources. Volatility could be quantified using standard volatility metrics. Also, over long periods, inflation will be addressed by normalizing the data to nominal values or adjusting ticket revenue accordingly.

- **Fuel Hedging Strategies**:
  May be included as a cost stabilization factor and compared to potential electricity price hedging. The model could show the benefits of hedging by showing results with and without stabilized electricity or jet fuel prices. This research will likely not include hedging as a decision variable in the model due to the scope of this research.

These insights will improve the model's ability to simulate jet fuel-based aviation performance, focusing on cost variability, regional pricing, and risk management. By establishing a robust jet fuel baseline, the model can effectively evaluate the economic feasibility of electric aircraft, emphasizing differences in price dynamics, network design, and operational strategies.

4

Energy Cost Management & Electric Aircraft

The intersection between fuel optimization and electric aircraft, without touching on airline planning, simply boils down to understanding electricity instead of jet fuel. This section will first elaborate on the unique characteristics of electricity, highlighting the factors that differentiate it from jet fuel. Next, it will explore how these characteristics influence price dynamics, particularly in terms of volatility and localization.

4.1. Electricity Pricing Specifics

In this section the key fundamental differences between electricity and jet fuel will be shown. These differences drive how the price behaves and the different effects of locality and volatility. Understanding the core fundamentals of electricity will help us understand why electricity prices behave differently from jet fuel, and thus why this research can produce novel and interesting results when jet fuel-optimized approaches have already been conducted.

Before diving into these aspects, it is important to distinguish between energy and electricity. Energy is a broad concept that includes various forms, such as chemical (fossil fuels such as jet fuel), thermal, and kinetic energy. Electricity, on the other hand, is a specific form of energy that must be generated, transmitted, and then stored or used. This research focuses on electricity prices.

The following list shows the key fundamental characteristics of electricity and how they differ from jet fuel:

- **Limited storage:**
  Electricity is extremely perishable which requires it to be used only as it is produced. It cannot be easily stored in large quantities, as storage methods are expensive, incur conversion losses, and are limited in size. Jet fuel, on the other hand, is not perishable and is frequently stored in large quantities in many locations. This will drive the volatility of electricity prices on the short term.

- **Transportation losses:**
  Electricity is lost during transport from producer to consumer, unlike oil-based fuels. Electricity transport typically occurs at high voltages over a transmission grid for long distances, then at a lower voltage over a distribution grid for the last mile [130]. Transmission grid losses range from 0.5 to 3%, while distribution grid losses vary between 2-14%, with higher losses attributed to lower voltage [130]. Assuming that airports can bypass distribution grids and connect directly to the transmission grid, only transmission losses should be considered. As distance increases, so do the transmission losses. These losses are estimated at 3% per 1,000 km for High Voltage Direct Current (HVDC) and 7% per 1000 km for High Voltage Alternating Current (HVAC), with

HVAC subsea cables experiencing even greater losses [131, 132].

In contrast, jet fuel, typically transported by pipeline or ship, incurs most of its losses during transfer between systems and through evaporation. However, the standard assumed loss rate in the Netherlands is only 0.3% [133], a number negligible compared to the losses of electricity transmission. Another difference is that electric power transmission losses are not equal per country. Globally, losses in electric power transmission and distribution averaged 8% of total production, but this varies significantly by country. For example, India averages 21% transmission loss, while Germany averages just 4% [134]. This difference will drive the localization of electricity prices.

• **Weather reliability:**
While the EU as a whole is committed to green electricity production (66% by 2030) and is steadily progressing toward this goal (44% as of Feb 2024 [135]), individual countries are at different stages due to varying political approaches. As a result, the composition of electricity production differs significantly between member states [136, 137]. The vast differences in the energy mix per country in the EU are shown in Figure 4.1.
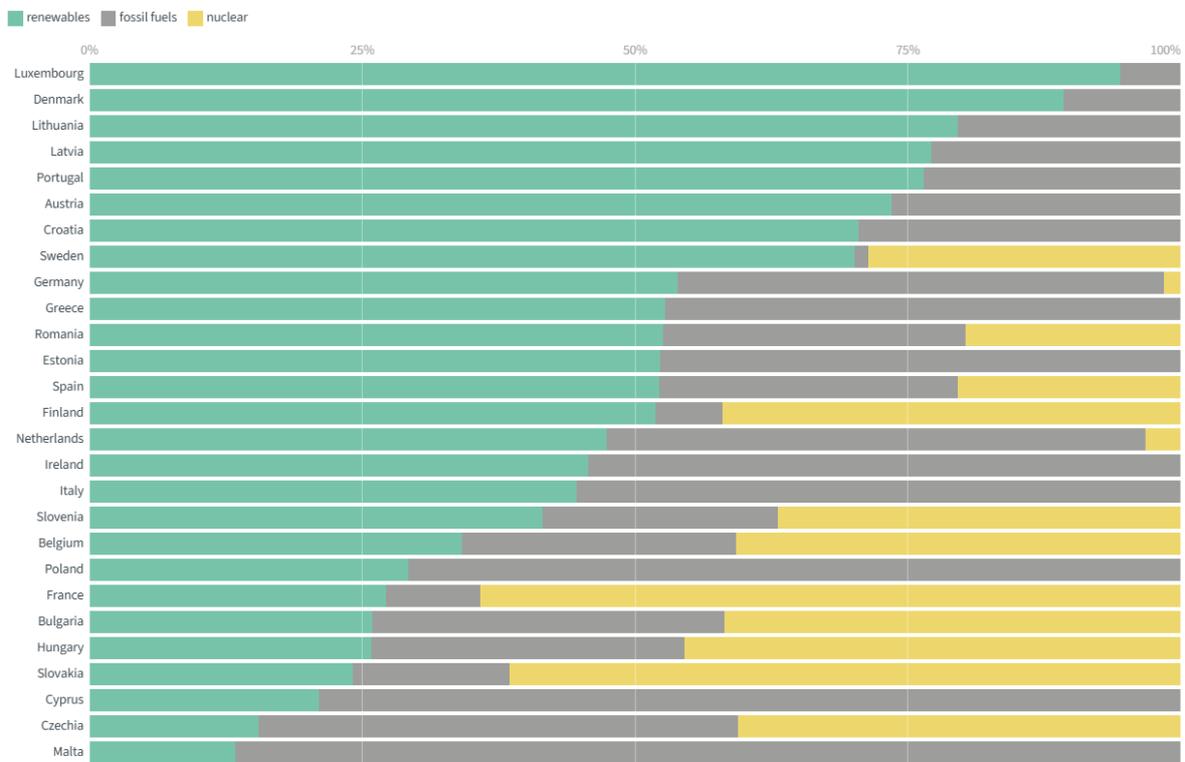
Figure 4.1: EU Energy Mix (2023) [138]
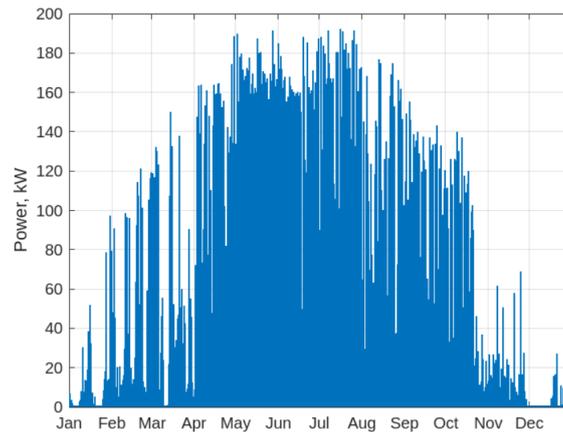
Figure 4.2: Power output from the solar PV system at JKG over 2023 [70]

The increasing share of renewable energy also increases the sensitivity of power production to weather effects [139]. Unlike nuclear energy, which provides a stable and controllable electricity supply, sources such as solar and wind are weather-dependent, making them less predictable. In addition, extreme weather events can further affect the reliability and efficiency of power sources such as hydro, solar, and wind energy [140]. Mosquera-Lopez found that the sun and wind have a statistically significant effect, especially in countries with high solar or wind capacity, with the minimum amount of the 10% share of the energy mix [141]. They also found that the relation ship is not simply linear but instead has minimums and maximums which can be coupled back to, for example, at which maximum wind speed turbines start being shut down for safety. Vehlhaber recognizes this dependence on weather and incorporates weather forecasts into its model aimed at optimizing flight scheduling and energy management in electric aviation networks by minimizing grid dependency [142].

Seasonal weather effects could influence the weather for months and affect planning at a higher strategic level. This can be seen, for example, in the solar production per month from a case study in Sweden (Figure 4.2).

There are also longer trends in weather, global warming, that can be seen at a higher strategic level. The weather can therefore significantly affect the electricity prices per location, further driving the localization and volatility of electricity prices.

- **Weaker correlation to crude oil:**
  Jet fuel prices exhibit a strong correlation and co-movement with crude oil prices, as aviation fuels are directly derived from crude oil [143, 144]. This is evident in the crack spread between crude oil and A-1 jet fuel, which remains stable at approximately $15 over time (Figure 4.3) [114].

Brent crude oil price with futures curve, jet fuel price, and jet crack spread, USD per barrel
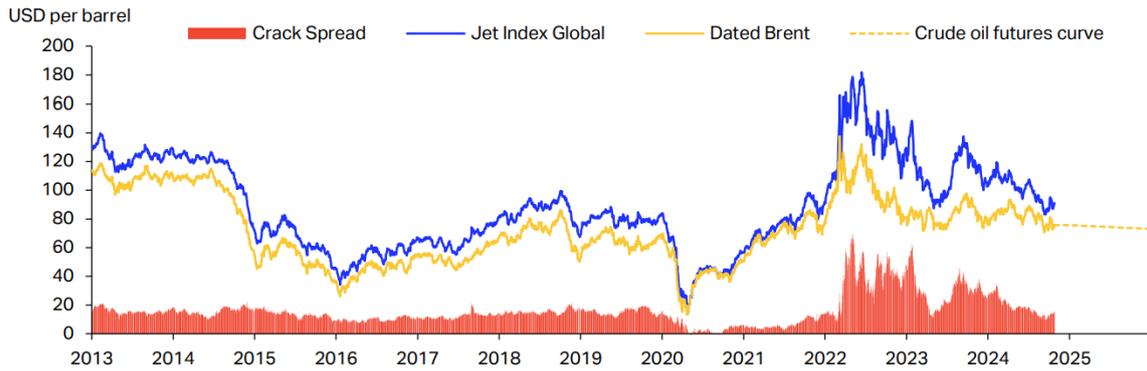
Figure 4.3: Crack spread for A-1 jet fuel [114]. The crack spread is the price difference between a barrel of crude oil and refined petroleum products, here A-1 jet fuel [145].

In contrast, electricity prices are far less sensitive to crude oil fluctuations, as oil is rarely used for power generation except in remote regions [136, 137, 146].

Figure 4.4 illustrates this decoupling, showing that electricity prices are less volatile and follow different trends compared to crude oil [147]. Instead, electricity prices exhibit a correlation with natural gas prices due to marginal pricing in electricity auctions, where flexible gas plants that are turned on last often set the market clearing price [148, 146]. However, this correlation is dependent on the energy mix of a country and diminishes when averaged across a continent, as shown in Figure 4.4. Gas-dependent countries such as the Netherlands exhibit more sensitivity to gas prices, as seen with the tripling of electricity prices due to the quadrupling of gas prices [149]. In addition to this, infrastructure-related costs further buffer electricity prices from gas price swings [146].

A contrasting opinion comes from Menezes et al., who showed that long-term dynamics of electricity prices are expected to reflect fuel prices, since, according to Menezes, fuels generally account for a large share of the cost of generation [150]. However, Menezes also recognized that as countries move toward sustainable energy sources, this link is likely to erode.
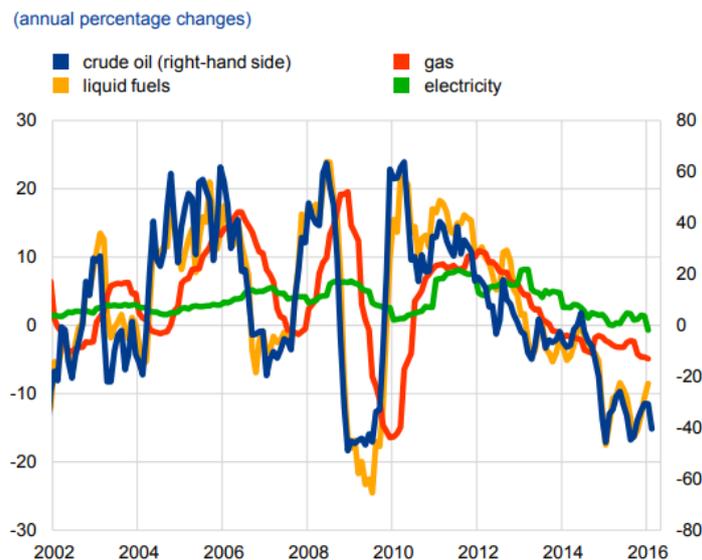
Figure 4.4: EU Crude oil prices and consumer energy price components from 2002-2016 [147].

Due to these dynamics and different production methods, electricity prices are largely independent of crude oil [147]. Consequently, optimizing flight networks for electric aircraft based on electricity prices will likely yield a different network that reacts differently to real-world events compared to current jet fuel-based networks.

- **High consumption discounts and high power surcharges:**
  In Europe (EU27), electricity prices for the second half of 2020 varied significantly by how much a user consumed annually, also referred to as the usage band. For the lower band (called IA) (<20 MWh annually), the cost was € 0.2485 per kWh, while the highest band (called IG) (>150 GWh annually) was 67% cheaper at € 0.0806 per kWh. Large airports, with their energy-intensive buildings, typically consume 100 to 300 GWh annually [151], placing them within or near the highest bracket. The energy demands of Electric Aircraft will further increase consumption, adding megawatts of daily usage to airports [152], cementing future airports even more as extremely large energy consumers. Smaller airports might not reach the highest bands so an increased electricity price should be modeled when operating from those.

  Although airports secure discounts for purchasing large amounts of jet fuel, they are unlikely to match electricity discounts, with estimates ranging from 10–20%; however, no precise data on typical jet fuel discounts are publicly available.

  It is important to note here that these discounts count for high energy draw and not for high power draw. Utility companies often charge demand based on the highest power draw in a billing period, often 15 minutes [153]. This is also referred to as a demand charge. Essentially, using a lot of energy steadily throughout the year can make it cheaper, but using a lot of energy in a very short time with high maximum powers can be very expensive. Many papers aim to reduce the maximum power draw induced by charging many AEA aircraft [152].

  While minimizing peak power demand is financially critical, it falls outside the model's strategic scope.

- **Unpredicted usage penalties:**
  Purchasing industrial electricity is a critical business consideration for many large electricity consumers. Factories aim to accurately forecast their electricity needs to secure discounted rates in advance. This practice provides network operators with better estimates of future demand, enabling more efficient utilization of production capacity. However, exceeding the pre-agreed consumption forces providers to unexpectedly increase output, relying on fast production methods that can be quickly activated and deactivated. This results in a far higher price for the consumer who ordered more than [154]. AEA can significantly increase the power draw in an airport, especially if all are charged at once. Therefore, delays or diversions could cause unexpected increases in power consumption, resulting in higher costs due to late order of electricity. In contrast, although jet fuel shortages can occur, the storage capabilities of jet fuel make such supply shortages extremely rare and less immediate.

- **Regulatory and tax:**
  Electricity taxes vary greatly between countries. Even within the EU, taxes and subsidies cause significant differences in effective electricity prices. Differences in tax policy and their effect on non-household electricity prices are shown as a total number Figure 4.5 and as a percentage Figure 4.6. Potential future carbon taxes could add yet another layer of variability to this by adding taxes dependent on how the electricity was produced.

Electricity prices for non-household consumers, first half 2024 (€ per kWh)
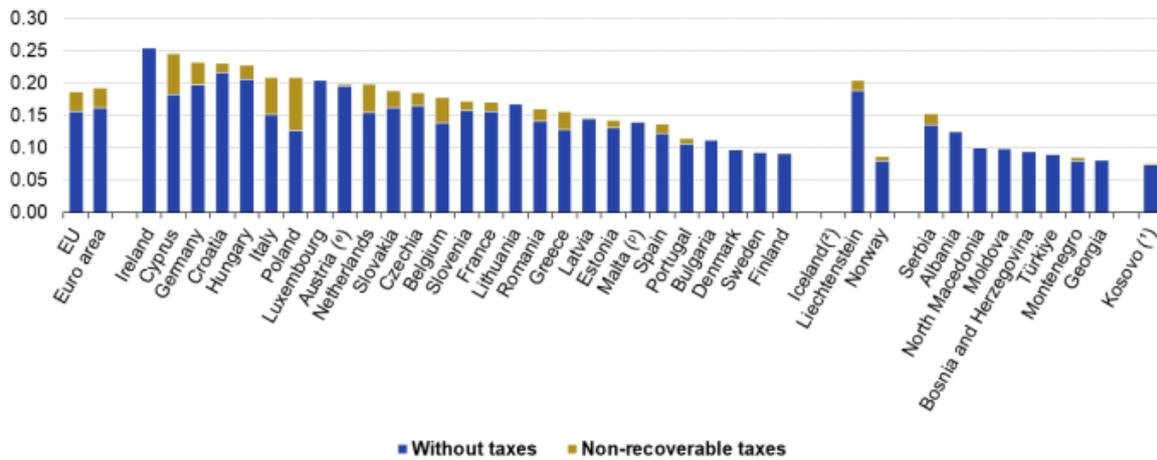
Figure 4.5: Electricity prices for industrial users in the first half of 2024 including local taxes and subsidies [155]

Share of taxes and levies paid by non-household consumers for electricity, first half 2024 (%)
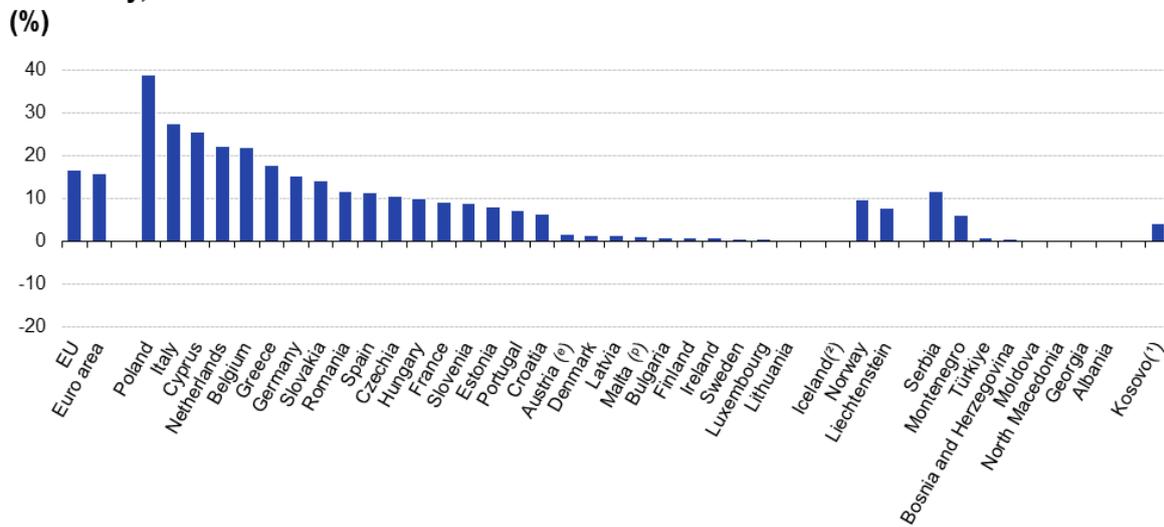
Figure 4.6: Share of taxes in electricity prices paid by industrial users in the first half of 2024 [155]

In contrast to electricity prices, in the EU, all jet fuel used for flights in and out of the EU is exempt from excise taxes by the EU Energy Taxation Directive [156, 157, 158, 159, 160]. Although EU

member states are allowed to tax jet fuel for domestic and intra-EU flights starting in 2003, as of 2019, no state has done so, only the Netherlands briefly applying a domestic tax [123]. The exemption of taxes further reduces the differences in jet fuel per country and represents another way in which electricity prices are more local than jet fuel prices.

Although some studies use the base price of electricity without added tax and fees (referred to as the spot price) [70], this research is likely to use the end-user electricity price for non-household consumers, since that is what airports and airlines will eventually have to pay. It will also help highlight differences in electricity tax policy and their effect on the flight network.

As can be seen from the above-listed arguments, electricity production differs fundamentally from jet fuel production. This has resulted in more localized electricity prices. Although many studies suggest that electricity prices are less volatile than jet fuel prices, a detailed comparison remains scarce.

4.2. Electricity Price Volatility

Electricity prices fluctuate significantly within one day, peaking as people wake up, commute and return home. Figure 4.7a illustrates the average weekly spot price in Sweden's SE3 bidding area for 2023, showing consistent patterns interrupted only by holidays. Unfortunately, passenger air traffic demand follows a similar curve.

While Figure 4.4 depicts stable EU-wide electricity prices, this reflects an average across countries. Zooming into one region in Sweden, as shown in Figure 4.7b, reveals high volatility in spot prices.

(a) Average weekly spot price of bidding area SE3 in 2023 [70]

(b) Electricity spot prices for 2023 in bidding area SE3 [70]
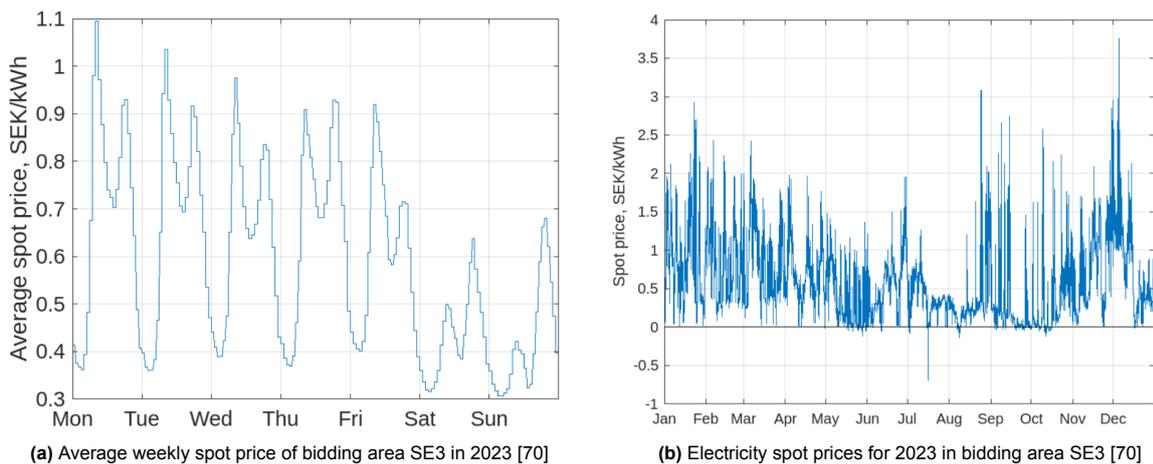
Figure 4.7: Comparison of electricity price trends in SE3 for 2023.

The more you zoom out, the lower the volatility tends to be due to the averaging out of differences. However when looking at countries there is still a measurable difference in volatility. Volatility varies widely across Europe, from 0.128 in Greece to 0.414 in Finland, due to diverse electricity production infrastructures [120]. Cevik et al. measure volatility as the standard deviation of the natural logarithm of price returns over 15-minute intervals. Comparable public data for jet fuel price volatility is unavailable.

4.3. Electricity Price Localization

Factors listed in section 4.1 drive localized electricity prices, varying between and within countries. This is evident when comparing Figure 4.8a (electricity) and Figure 4.8b (diesel), where countries like Denmark and Czechia shift in relative cost.
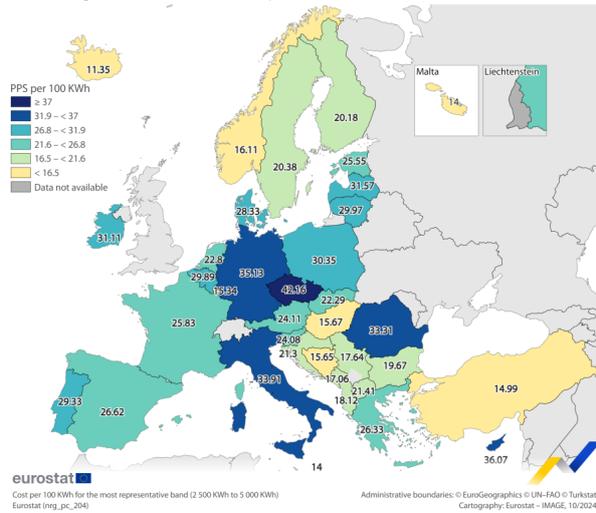
(a) EU Electricity Prices 2024 S1 [155]
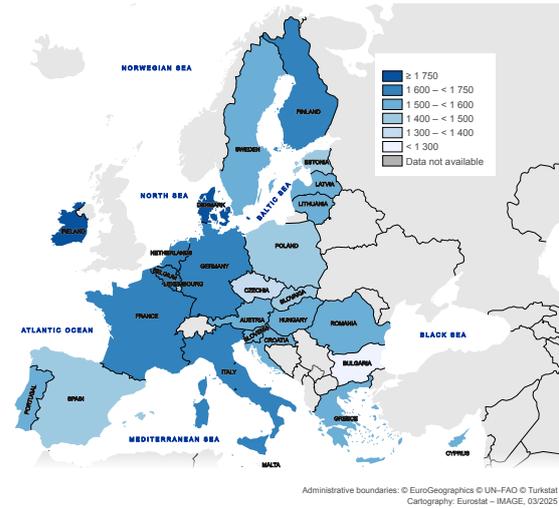
(b) EU Diesel Prices (27/03/2025) [124]

Figure 4.8: Comparison of EU energy prices: (a) Electricity prices, (b) Diesel prices.

Prices fluctuate yearly. In the first half of 2024, electricity prices in Ireland and France rose by 21% and 37%, respectively, while Belgium and the Netherlands saw declines of 23% and 28% [155]. This highlights how factors in section 4.1 create localized pricing. Countries with low jet fuel costs do not necessarily offer cheap electricity, potentially reshaping optimal flight networks as electric aircraft prioritize regions with favorable electricity prices over jet fuel availability.

4.4. Relevance to this research

Understanding these price dynamics is crucial for modeling electric aircraft operations in Europe. Unlike conventional flight networks optimized for jet fuel costs, electric networks must account for localized and volatile electricity prices, influencing route planning and operational costs. As Europe's energy grids integrate further, both physically and through markets, price disparities may narrow [150]. However, the diverse production sources across countries ensure that significant price differences persist [137]. Understanding what moves electricity prices to be volatile or localized will help analyze and differentiate the effects that will have on an entire flight network.

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5

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Airline Planning

Airline planning is a complex multistage process critical to the operational and financial success of airlines, as extensively documented in the academic literature. More than 75% of the overall airline costs is estimated to be determined by the schedule [161]. For this reason, operational research has focused on this topic since the 1960s [162].

5.1. Flight Planning Steps

Airline planning is usually broken down and tackled sequentially in segments due to its computational complexity. The different subproblems of airline planning are generally addressed on a planning horizon spectrum from strategic, to tactical, to operational based on how long before departure the planning decisions are typically made. Strategic decisions are made 10 to 1 year in advance, tactical from 1 year to 1 month, and operational from 1 month to the day of departure [163].

In this planning horizon, airline planning is further broken down. This can be done in different ways and at different abstraction levels. In 1985, Etschmaier and Mathaisel broke it down into seven subproblems [164], more recent literature breaks it down into four [165, 166, 167], and Belobaba breaks it down into three subproblems [168]. The three problems are defined as follows:

- **Fleet Planning** (Strategic)

- **Route Planning** (Strategic)

- **Schedule Development**

    - **Frequency Planning** (Tactical)

    - **Fleet Assignment** (Tactical)

    - **Timetable Development** (Tactical, Operational)

    - **Aircraft Rotations** (Tactical, Operational)

The goal of airline scheduling is to create an airline schedule that is optimal with regard to a given objective, usually operating profit, although recent articles have often incorporated multi-objective functions to incorporate climate objectives [73].

The next sections will elaborate on each of the subproblems. Some problems are known by different names, in which case that name is shown in parentheses.

5.2. Fleet Planning

Fleet planning in commercial aviation represents the long-term strategic process of determining which types of aircraft are needed for future operations [169]. This process is fundamentally driven by passenger demand and is closely integrated with network planning, as fleet decisions depend on intended routes while route selection is constrained by available aircraft types. Aircraft selection is centered on payload range characteristics, where each type offers specific trade-offs between carrying capacity and operational range. This trade-off is further influenced by acquisition costs, operating expenses, and airport infrastructure constraints, including runway length and gate dimensions.

Fleet composition decisions include aircraft numbers, types, acquisition timing, and retirement scheduling. These have enduring consequences because commercial aircraft typically remain in service for decades, with a global average age of 11.6 years, and significant portions of the fleets tend to fly for up to 25 years [170]. Historical trends also reveal evolving fleet philosophies showing how fleet planning can be a bet on the future. For example, the A380 aircraft represented a bet on the demand for high-capacity aircraft, whereas current preferences favor long-range fuel-efficient models with larger but fewer engines [171]. To improve operational flexibility and reduce initial capital requirements, airlines frequently employ leasing arrangements despite higher long-term costs, with this approach now accounting for approximately 58% of the global commercial fleet [172]. Leasing agreements range from short-term wet leases (1-24 months, including crew and maintenance) to dry leases classified as medium-term operating leases (2-7 years) or longer-term finance leases (5-10 years) that appear on balance sheets [163].

The fundamental challenge in fleet planning lies in simultaneously optimizing two interconnected problems: identifying the ideal fleet composition for desired routes and passenger service.

5.3. Route Planning (Network Design, Route Development)

The design of the airline network represents a critical strategic planning step that determines from which airports to operate (node selection) and which specific routes to fly (route selection), sometimes referred to as the route development or network design phase [173]. In the airline network planning phase, the network design problem is generally formulated as developing a design for the network and routing policies of a single airline that satisfies the demand for the origin-destination (OD) of the passengers while minimizing the total costs of air transport and passengers [174, 175]. This process is primarily driven by market competitions and demands to be met, as well as by the overall structure of the network [161]. Technical restrictions such as range, runway length, ground facilities, and gate availability can limit available routes depending on the fleet composition. The main decision variable in route planning is a binary variable that indicates whether or not an available route will be serviced. Models are usually optimized on specific point-to-point route demands, but versions of the route planning problem also exist where the objective is to reach as many people, also known as the maximal coverage problem.

More specialized research has evolved to incorporate additional dimensions into network design analysis. Scholars have investigated the impacts of alliances on hub networks [176], incomplete network scenarios [177], and multimodal transportation integration such as with trains [178].

5.3.1. Network Structure

There are two main network structures: hub-and-spoke and point-to-point. Hub-and-spoke systems funnel traffic through central airports, enabling passenger flow consolidation to artificially increase demand per route [179, 180]. They are also more resilient against demand uncertainty [181]. In addition to this, hubs also allow the consolidation of airline maintenance resources. In general, point-to-point configurations excel with greater distances, robust demand, and limited destination counts, while hub-and-spoke arrangements perform better under inverse conditions [182, 183]. Traditionally, flag carriers tend to operate hub-and-spoke structures, while low-cost carriers (LCCs) prefer point-to-point. Laumann et al. view the network structure as a trade-off between reducing passenger comfort, which might decrease revenues, and reducing jet fuel consumption [125]. The choice of network structure is also dependent on the fleet composition and can influence fleet assignment since larger aircraft usually use less jet fuel per passenger but are only beneficial when there are sufficient passengers to fill the aircraft[125].

Therefore, it might be necessary to route passengers through hubs to increase demand by merging flights.

5.4. Schedule Development

Schedule development encompass both tactical and operational subproblems. Its final aim is to develop a complete minute-by-minute schedule for every aircraft in the fleet. This starts with frequency planning, followed by fleet assignment, time table development, and aircraft routing. These steps are organized together under schedule development because they are very connected and interdependent.

5.4.1. Frequency Planning (Flight Frequency Problem, Route Frequencies)

In the frequency planning step, the routes selected during route planning are analyzed to determine the number of flights per time period required to meet demand. The primary decision variables are the number of flights per route, although this is often split up into the number of flights per route per aircraft type [184], thereby incorporating fleet assignment as well. This flight frequency problem has traditionally been solved sequentially to manage model complexity. However, recent advances in computational power have enabled the adoption of integrated models that offer superior performance. Frequency planning is frequently combined with route selection, as a zero frequency implies a route should not be selected, and with fleet assignment, since passenger servicing capacity depends on both flight frequency and aircraft capacity. De Jesus et al. [185] explored such an integrated model in the Brazilian regional aviation market, proposing a novel approach to optimize flight frequency and aircraft capacity prior to aircraft acquisition. Also note that some research uses schedule design to refer to frequency planning [125, 186, 187]. For a more in-depth analysis of frequency planning models, a comprehensive summary is provided by Hsu et al. [184].

5.4.2. Fleet Assignment

Fleet assignment is a tactical planning step that involves allocating aircraft families and types to flight routes to optimize operational efficiency, often modeled as a multicommodity flow problem [169]. The primary goal is to align the fleet with route-specific demands and ranges in order to maximize profit. This is often done by minimizing operational costs and spilled demand and maximizing revenue from served passengers. Again, technical constraints such as aircraft range, runway length, ground facilities, and gate availability restrict feasible routes for each aircraft type.

An aircraft family comprises specific aircraft types sharing common airframes, maintenance procedures, and pilot type ratings, allowing flexibility in assignments. Typically, airlines determine the aircraft family for a route 10-12 weeks before departure to allow crew assignment 4-8 months before departure [169], while the exact aircraft type may be finalized 4-6 weeks before takeoff [188, 189]. This staged approach allows for late reassignments to better suited flight legs to improve efficiency as more precise demand data emerge [190]. Airlines employ proprietary optimization models to balance these factors, ensuring that fleet assignment effectively meets operational and revenue objectives. For a holistic review of fleet assignment models, a comprehensive summary is provided by Sherali et al. [191].

5.4.3. Time Table Development (Flight Scheduling)

The development of the time table determines optimal departure times for flights, and sometimes arrival times, to construct a detailed operational schedule. This step is computationally intensive due to its often minute-by-minute granularity, making it a challenging aspect of airline planning. To address this, airlines often adopt an incremental approach, adjusting the schedule for the next season based on previous ones rather than creating a new schedule from scratch. This method reduces complexity and maintains service consistency, fostering passenger trust in predictable flight timings [169]. The availability of airport slots serves as a critical constraint shaping these schedules.

One way the process can be modeled by selecting from a set of predefined flight legs with assigned times, streamlining optimization efforts. In addition, a time-space network is often used to capture possible connections between arriving and departing flights, offering a robust framework to schedule within a day [192, 188]. To reduce computational demands, researchers often use coarser time windows, such as 15 or 30 minutes, when exact minute-level planning is not the primary focus. For a more in-depth

study of time table development, Etschmaier et al. is often cited as foundational overview of schedule construction and evaluation techniques [164].

5.4.4. Aircraft Rotations (Aircraft Routing)

Aircraft routing assigns specific aircraft to a sequence of scheduled flights from the timetable, typically finalized 1-2 weeks in advance (with a draft routing prepared earlier)[169], ensuring that each flight is covered by one aircraft while meeting maintenance and operational constraints. With fleet assignment already completed, the problem can be segmented by aircraft type, framing it as a dynamic network challenge that balances routes over time and space. The objectives include minimizing operating costs, maximizing maintenance opportunities and ensuring flight coverage, route continuity, aircraft availability, and balanced utilization, while adhering to minimum turnaround times and airworthiness requirements [163]. Periodic light maintenance, typically every 3–5 days at designated stations, further shapes routing, with airlines building schedules that incorporate frequent maintenance opportunities and slack times to comply with regulations. Note how periodic return to a maintenance base after a set amount of flight hours is similar to the more frequent but still periodic return of electric aircraft to a base with charging equipment.

5.5. Integrated Planning

Airline planning has traditionally been addressed sequentially, from strategic decisions like network design to operational tasks like aircraft routing, due to computational complexity. However, this approach often produces suboptimal solutions due to interactions between planning steps, where a solution to one subproblem may not yield a feasible outcome for others. To address this, recent research has explored integrated airline scheduling models that combine multiple steps to enhance solution quality and airline profitability. Now is also a good time to define the two axis on which most airline planning models can be placed: integratedness and comprehensiveness.

With a comprehensive approach, this paper refers to a method that tackles all or nearly all major subproblems of the airline planning problem that are relevant in this paper. This primarily includes: Fleet Planning, Route Planning (network design and route selection), Schedule Development (route frequencies, fleet assignment, flight scheduling, aircraft routing). With Electric Aircraft, this extends to charge sitting, charge sizing, and charge scheduling which will be explained in chapter 6. Subproblems such as maintenance planning, crew allocation, and disruption management are left out of the scope of this research and thus not included in the way this paper defines a comprehensive approach or problem.

Integrated is defined as a method that optimizes multiple sub-problems of the airline planning problem in a single model. A two-stage model that solves subproblems sequentially is thus not an integrated model, although it could be defined as comprehensive if it tackles all or nearly all of the relevant subproblems.

5.5.1. Integration in literature

Integration can happen at different levels of comprehensiveness and thus involve pairing two or three sub-problems or pursuing fully comprehensive models. Some pairs of subproblems are tightly intertwined and thus are more frequently solved integrated together. For example, fleet assignment and fleet planning are integrated, with Dozic et al. [193] proposed a model that jointly optimizes fleet size and assignment using a variable neighborhood search method . Fleet assignment and timetable development are also often combined. Kenan et al. [194] do this and use a sample average approximation algorithm to manage the many optional flight legs and airport conditions that arise from this integration. Aircraft routing and timetable development are also often paired, with Jamili developing a robust model solved via simulated annealing to address both simultaneously [195]. Route planning and frequency planning are also linked, often integrated to align network and service decisions. These pairings leverage the influence of one step on another. Full integration remains computationally challenging but is increasingly being tackled.

5.5.2. Relevance to this research

Understanding airline planning models and their interconnections is essential for this study, which seeks to develop and extend frameworks that address multiple subproblems in the context of electric aircraft

operations in Europe. Strategic steps like fleet planning, route planning, frequency planning, and fleet assignment are particularly relevant, as they shape the feasibility of integrating electric aircraft into existing networks, and are underrepresented in research, as will be elaborated in chapter 8. In contrast, tactical and operational subproblems like timetable development and aircraft rotations, while critical for day-to-day execution, are less emphasized here, as prior research has already explored their application to electric aviation.

Insights into planning timelines also hold practical value. For example, the finalization of fleet assignment occurs 4-12 weeks before departure, offering a window where updated electricity price forecasts could refine decisions. This suggests potential benefits of replanning certain steps as more accurate data emerge.

5.6. Demand Modeling

Demand modeling serves as a critical foundation in airline planning, acting as the primary mechanism to balance cost minimization with profitability optimization [196, 197]. It ensures that airline planning aligns with the source of revenue: the passenger travel needs. Demand modeling is extremely relevant for this research since it will be the counterweight to minimize recharging costs. Routes with cheap recharges but low demand will have to be balanced against routes with higher demand but more expensive charging. This section highlights the key aspects of demand modeling, including its expressions, challenges, methodologies, limitations, and applications in airline planning.

5.6.1. Expressions of Demand

Passenger demand can be articulated in three overlapping yet distinct ways:

- **Origin-Destination Demand (OD)**: Total number of passengers who want to travel between two points, regardless of the specific routes or flights they take [174, 175].

- **Itinerary Demand**: Total number of passengers who want a particular sequence of connected flight legs that form a complete journey [198, 189].

- **Point-to-Point Demand (P2P)**: Total number of passengers who want to travel an individual flight leg, regardless of the final destinations of the passengers.

These perspectives offer different benefits and drawbacks, allowing airlines to tailor their planning processes to different operational and strategic needs. Most solution methods and models are tailored to one specific type of demand formulation. For example, there are standard fleet assignment models using P2P demand and there are itinerary fleet assignment models (IFAM).

5.6.2. Sourcing Demand Data

Many studies choose to avoid the time and effort required for a precise demand estimate and rely on publicly available flight data, such as schedules or the number of flights between airports, to infer a rough approximation of demand. Schedules are often retrieved indirectly through tracked flight data from sources such as FlightRadar24 [103]. Demand can also be extrapolated from historical demand data with techniques such as time series projections or even machine learning methods such as ridge regression, random forests, and neural networks [163]. More accurate historical demand data, while offering greater detail, is often proprietary to airlines and remains limited in its applicability to new routes or underutilized airports [13]. To address these shortcomings, researchers and planners frequently turn to demand simulation and causal methods, a process encompassing two primary stages:

1. **Demand Generation**: Estimate the total travel demand between locations.

2. **Demand Allocation**: Distributing this demand across available travel options.

5.6.3. Demand Generation

Demand generation is the act of calculating where passengers are and how likely they are to travel. It is typically modeled using gravity-like formulations which are are usually based on factors such as:

- **Geo-economic Factors**: Such as GDP and population size.
- **Impedance Factors**: Including distance between locations.
- **Service-Related Factors**: Like flight frequency and itinerary options.

Notable studies by Grosche et al. [199], Boonekamp et al. [200], and Birolini et al. [201] have refined these models to predict passenger volumes effectively. Kinene et al. and Justin et al. [13, 202] employ similar demand generation techniques in their papers on electric aircraft airline planning.

5.6.4. Demand Allocation

Once generated, demand can be allocated among competing travel options which include the flights but also sometimes other transport methods such as cars and trains. Modeling which transport method someone is most likely to choose is done using choice models. These models evaluate passenger preferences based on attributes such as airfare, flight frequency, and travel times [13]. When deciding between different modes of travel and their respective utility, the famous s-curve appears, as can be seen in figure Figure 5.1. Some of the results of the demand allocation step of the same paper are shown in Figure 5.2 for the case study in North-East United States. This figure shows that when the door-to-door distance is longer than about 250 miles (400km), almost everybody prefers to fly. This causes the model to allow for fewer flights under 250 miles than above, since the demand is much more limited. Such a model would be very helpful in this research, but only if it could be used with minimal effort due to scope and time constraints.
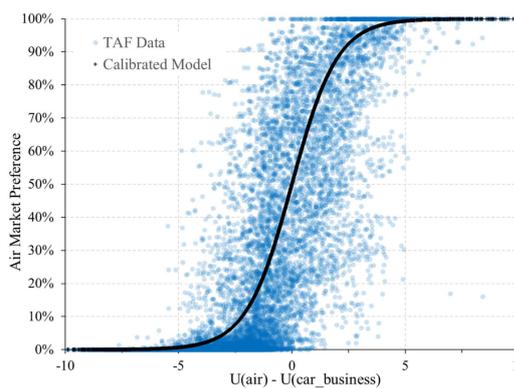
Figure 5.1: Air Market Preference by comparing the utility of air transport and car transport [202]
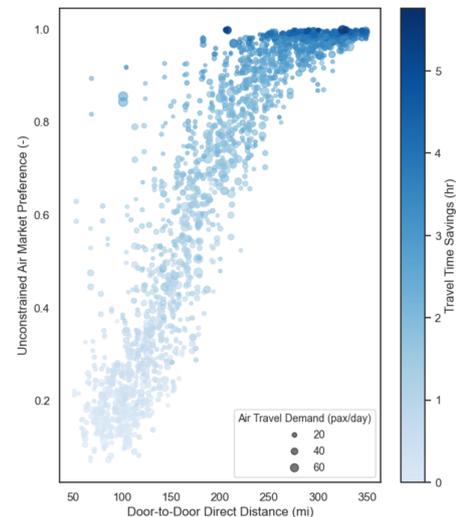
Figure 5.2: Market preference for nonstop air travel as a function of door-to-door direct distance [202]

Recent advances integrate the supply and demand interactions, allowing the demand to dynamically react to the flights provided by the model [203].

5.7. Relevance for this research

Demand techniques extend beyond this section, with numerous papers exploring advanced and accurate demand models. However, this research begins with basic knowledge about demand modeling, as demand simulation is not the focus. The initial step is to find usable public demand data that fit the research scope. If unavailable, advanced demand modeling may be needed, but that will depend on the availability and completeness of the data.

<div style="text-align: right; font-size: 4em;">6</div>

Airline Planning & Electric Aircraft

Electric aircraft have introduced new planning challenges for future electric airlines to tackle. These problems can be divided into air- and land-side planning problems. The airside concerns itself with all aircraft operations in the air and overlaps largely with traditional airline planning problems. Landside planning is concerned with infrastructure planning and scheduling. In this area, electric aircraft have created novel planning challenges around charging the aircraft.

This chapter will elaborate on airline planning research for electric aircraft. It will first do so by giving an overview of papers that tackle the landside problems and then move on to airside related problems since they often include elements of the landside problems. Note that the line between airside and landside problems is not always as clear as some research attempts to do parts of both.

6.1. Start in Electric Vehicle Research

Much of the research for EA is an expansion of research done for EVs. For example, early EV research investigated the strategic placement of charging infrastructure [204] and the operational management of battery swapping stations under uncertain electricity prices and demand [205, 206]. In addition, studies explored the route of electric vehicles to charging facilities, taking into account the time of use of the electricity price [207]. With some adjustments, this research was adapted to AEA.

More related to this research, Ham et al. addressed the Electric Vehicle Routing Problem with Time Windows (E-VRPTW) under Time-of-Use (TOU) electricity prices for electric vehicle services such as robo-taxis [208]. The model effectively considers hourly electricity prices but does not localize this price. These advances centered on electric vehicles laid the groundwork for subsequent recharging and planning strategies for the EA. For a recent review of the research on EV charging relevant to AEA, see Leijon et al. [209]. For a review of electric vehicle routing models specifically, see Erdelic et al. [210].

6.2. Landside Planning

The electrification of aviation represents a series of new challenges for the airline industry. The goal is to allow high utilization of electric aircraft through short turn-around times while minimizing both initial infrastructure investment costs and long-term operational costs. Novel aspects include minimizing maximum grid power draw, with research by Lindberg et al. [211] at Skelleftea airport revealing weekly increases in electricity demand of 56- 104% throughout seasons and increases in peak power requirements of 167- 333% with electric aircraft operations. Further studies by Van Oosterom et al. [212] demonstrated charging power requirements that exceeded 4.4 MW in larger airports. These substantial impacts on the infrastructure require comprehensive optimization of the electrical system. In a similar way to how airline planning can be broken down into its component problems, the different infrastructure land-side related problems for electric aircraft can generally be categorized into the following

problems.

- **Charge Siting:** This strategic problem involves optimizing the placement of the charging infrastructure in airport networks. It is similar to a maintenance hub placement problem except that it requires far more frequent visits. Existing studies that focus on other problems simplify this by assuming ubiquitous charging availability at all airports or only at major hub airports.

- **Charge Sizing:** This strategic challenge includes determining the type, quantity, and power capacity of chargers required at selected sites. Research frequently investigates hybrid configurations that combine multiple types of charger for synchronized operation to balance efficiency and cost. Key approaches include [211, 70]:

  – **Plug-in Charging System (PICS):** A conventional cable-based method akin to electric vehicle charging. PIC offers simplicity and compatibility with fixed aircraft battery designs, but its prolonged charging duration limits operational throughput.

  – **Battery Swaps System (BSS):** This involves replacing depleted aircraft batteries with precharged units, allowing for rapid turnaround times (30 min [70]), off-peak charging of spares, and limit battery degradation [213]. However, it requires aircraft designs with modular and swappable batteries, a standardized battery design to build economies of scale, and a surplus battery inventory proportional to flight schedules, increasing capital costs.

  – **Mobile Charging Station (MCS):** A flexible plug-in solution using mobile battery units (e.g., truck-mounted), decoupling charging from real-time electricity pricing and helping decrease maximum power draw. Despite its versatility, MCS incurs higher costs due to additional battery requirements, resembling a Battery Energy Storage System (BESS) deployed at airports.

- **Charge Scheduling:** An operational problem focused on determining optimal charging times for incoming aircraft and spare batteries. This process typically minimizes flight delays and electricity costs by leveraging time-of-use tariffs and operational constraints, although specific methodologies vary between studies. A large focus here is also minimizing the maximum power draw to prevent high and expensive peaks.

Landside electric aircraft planning encompasses various aspects, but current research focuses primarily on three key areas. Challenges such as battery health maintenance planning are also important considerations.

6.2.1. Airport Infrastructure Sizing and Siting

The challenge of sizing and siting airport infrastructure for electric aviation (EA) begins with optimizing charging station placement, a problem Kinay et al. [214] tackled by focusing on electric vehicle charging needs. Their approach minimizes both station costs and total recharging requirements while ensuring all origin-destination pairs can complete trips without battery depletion. To achieve this, they employed a Benders decomposition algorithm enhanced with optimality cuts, accelerating solution times up to 900× compared to standard solvers. This allowed them to efficiently solve a case study with 1397 nodes, setting a practical benchmark for large-scale infrastructure planning.

To address the need for optimized infrastructure, researchers have developed complementary approaches, often collaborating to refine airport EA solutions. Salucci et al. [215] tackled the selection of charging methods early on, weighing battery capacity and power limitations to design infrastructure that adapts to airport size and flight schedule density. Of particular relevance for this research, their model also generates optimal charging schedules using two electricity prices: high daytime and low nighttime. The authors likely chose not to model more dynamic electricity prices to limit the complexity of the model and possible prevent non-linearity effects.

Frequently working alongside Salucci, Trainelli et al. [41] later introduced the ARES (Airport Recharging Equipment Sizing) tool, establishing a foundational framework that determines optimal charging points, electrical consumption profiles, and recharging schedules while minimizing costs for both plug-in and

battery-swapping approaches. Together, their collaborative efforts highlight a path towards tailored, cost-effective charging solutions.

As the field evolved, researchers began to address more specific constraints, such as limited grid capacity at regional airports. Vehlhaber et al. [60] advanced infrastructure sizing by focusing on locally produced electricity to support fleet-wide EA charging where grid resources fall short. Using a mixed integer linear programming (MILP) approach called the *electric Aircraft Routing Problem* (eARP), they started with a fixed, fully electrified flight schedule and determined optimal aircraft-to-flight assignments. Their model accounts for energy constraints, charging needs, and infrastructure limitations across the network, incorporating Battery Energy Storage Systems (BESS) that was found to pair effectively with unreliable renewable energy production. A key finding was that oversized EA batteries larger than needed for the routes imposed an energy penalty due to excess weight. In their Dutch ABC islands case study, optimally scaled batteries reduced total extra costs by 17%, highlighting the importance of aligning infrastructure with operational realities.

While these studies optimized infrastructure design, operational implementation emerged as another critical dimension. Doctor et al. [74] applied discrete event simulation to explore how airports could integrate EA into existing layouts. They discovered that converting only 13% of the parking stands could support 25% fleet electrification without compromising efficiency. Their analysis also compared turnaround times for kerosene versus electric aircraft, evaluating single-use stands (electric or kerosene only) versus dual-purpose stands (both). This practical focus on retrofitting complements the strategic planning of previous works, bridging the gap between infrastructure planning and actual implementation into current infrastructure.

Finally, Holmberg [70] addressed long-term economic viability with a 10-year cost analysis of charging systems. As shown in Figure 6.1, electricity costs dominate over time, underscoring the need for careful price planning. The plug-in charging system (PICS) incurs high grid extension costs due to peak power demands that require substantial upgrades. In contrast, Battery Swapping Systems (BSS), both off-peak (BSS-OF) or on-peak (BSS-ON), use batteries to smooth electricity price fluctuations, reducing sensitivity to peaks and lowering costs. This showed the interconnectedness of infrastructure design, energy management, and operational strategy, providing a holistic view of EA adoption from a landside infrastructure perspective.
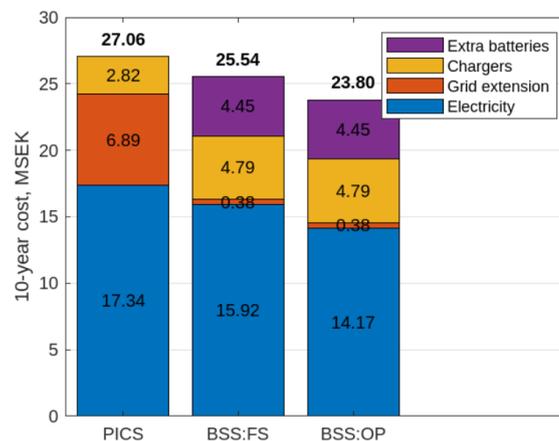
Figure 6.1: Total cost of each charging system over ten years, sorted by cost category [70]

6.2.2. Charge Scheduling

Aside from optimizing charger Siting and sizing, research has also been done into optimizing charge scheduling which entails when to charge which aircraft or which spare battery. This started by using fixed flight schedules and was then expanded by allowing slight modifications to them to lower grid power peaks. Later this evolved to fully integrate with flight scheduling. In subsection 6.3.4, more integrated models that fully integrate flight scheduling with charge scheduling will be highlighted.

Starting with a fixed schedule with the goal of maintaining schedule integrity, Justin et al. [216] focused on charge scheduling and proposed two strategies to optimize battery swap and recharge operations for thos batteries. The model is both a power-optimized strategy to minimize peak power draw and electricity costs, and a power-investment-optimized strategy that balances electricity costs with capital expenditures for batteries and chargers. The problem was decomposed into two steps: first, determining feasible combinations of chargers and batteries, and then generating optimal recharge schedules. When applied to the operations of two commuter airlines, their power-optimized strategy reduced peak power demand by up to 61% and electricity costs by up to 25% compared to a non-optimized approach. The power investment optimized strategy achieved slightly lower reductions in peak power (49-54%) but reduced overall costs by optimizing the trade-off between infrastructure investment and electricity pricing.

Also using a fixed flight schedule, Van Oosterom and Mitici [212] developed a more advanced model to size the charging infrastructure and capture daily price variations. Their recourse model optimizes three key variables: battery charging schedules, required number of spare batteries, and charging power capacity across airport hubs. The authors develop a hierarchical optimization approach consisting of a strategic planning phase for infrastructure sizing and a tactical planning phase for battery recharge scheduling. The objective function simultaneously minimizes flight delays, electricity costs, and infrastructure investment costs. The model provides insights into optimal battery charging strategies, balancing charging during off-peak electricity hours when possible while maintaining operational robustness. Their analysis also revealed that optimizing for an entire year of operations rather than just peak days reduces infrastructure costs by 7%, while optimizing for median traffic days would lead to excessive delays during peak periods. However, the model does not account for longer-term electricity price patterns, such as seasonal fluctuations.

The next step up from charge schedule models that use fixed flight schedules are models that allow small modifications to the flight schedules, thereby partially integrating it with the timetable development problem. This technique allowed the model size to stay small but does provide some schedule flexibility. Hou et al.[152] used this technique and focused on the integration of charging considerations with flight scheduling at major hubs such as JFK, revealing how smart charging and minor schedule modifications can dramatically reduce peak power demands and grid infrastructure needs. Similarly, Van Amstel [27] conducted a sensitivity analysis demonstrating that even modest flexibility in flight schedules (30 minutes) through time shifts and turnaround extensions yields up to 50% infrastructure cost savings. This research also found that solar energy and battery storage are more cost-effective than wind energy for airport energy generation on site to accommodate the extra demand of the AEA. The model accounts for variations in renewable energy generation and the use of local grid power, including opportunities to return surplus energy to the grid.

The next evolution are models where charge scheduling and flight scheduling are fully integrated. These models will be elaborated on in chapter 8.

6.3. Airside Planning

Airside airline planning encompasses the majority of classical airline planning research, but in doing so also tends to cover vast portions of the landside problem. This section will elaborate on airside operational research that has done both airline planning and uses Electric Aircraft, but does not actively consider fuel optimization. Any papers that include fuel optimization will be elaborated on in 8. The section will look at the three major subproblems of airline planning that are of particular importance to AEA operations.

6.3.1. Network Design

To effectively integrate electric aircraft into air transportation, the strategic foundation of airside planning begins with designing a robust network, including where charging infrastructure should be located. Kinene, Birolini, et al. [217] developed an optimization framework that focuses on the strategic design of charging networks for electric aircraft serving regional routes, determining which airports should be equipped with charging infrastructure (charge siting) while optimally balancing installation costs with regional connectivity and population coverage goals (network design). The paper does not address

tactical and operational aspects of air transportation such as route frequencies, fleet assignment, or flight scheduling, which the authors note would be decided in later planning stages after the strategic charging network was established.

Their Electric Aircraft Charging Network for Regional Routes (EACN-REG) model formulates the problem as a multiobjective facility location problem that balances the number of charging bases against regional connectivity and population coverage. Their case study of Sweden demonstrates that leveraging currently underutilized regional airports provides substantial connectivity and investment benefits (12.1% increase in regions covered, 5.8% more population coverage, and 7.3% reduction in travel times). Furthermore, increasing the maximum range of aircraft from 400 to 600 km requires 31 to 47% fewer charging bases while achieving 1% more coverage, creating more direct paths and increasing the resilience of the network.

This strategic focus on network design while also optimizing electric charging infrastructure lays the groundwork for subsequent decisions about fleet composition and operational scheduling.

6.3.2. Mixed Fleet Assignment

In the same way that the AEA network design incorporated a mixed bag of conventional and charging capable airports, the introduction of EA could likely be the first AEA will fly in mixed fleets with both conventional and electric aircraft. Chan et al. [218] explore the beginnings of this problem by considering the fleet assignment problem with a mixed conventional and hybrid electric aircraft (HEA) fleet. The most optimal HEA had only a conservative 3% electrification ratio, but it did yield slight cost reductions (0.996 cost ratio). The research found that, while operationally feasible, minimal cost savings likely do not justify high acquisition costs without future improvements in battery technology or sustainability incentives not accounted for in the model. The paper does not consider the variation of local electricity prices in the cost analysis of its hybrid fleet.

6.3.3. Flight Scheduling

Combining the previous problems, Mitici et al. [219] addressed the flight scheduling, fleet assignment, and charge scheduling and sizing subproblems of electric aircraft operations, while not tackling network design, route selection, route frequency, or charge Siting problems, assuming charging infrastructure would only be available at hub airports. The authors developed a two-phase mixed-integer linear program that first determines optimal fleet investments and flight schedules given a flight demand and then calculates the required charging infrastructure and charge schedules. The approach is not fully integrated due to its two-phase design. Charge Siting was left out of the picture by assuming that only the hubs could invest in sufficient charging facilities.

The authors also used a bilinear battery charging model that accurately reflects the charging behavior of lithium-ion batteries, where the charging slows significantly above 90% capacity, instead of the usual linear charging curve used. The results showed an optimal mix including both charging and swapping strategies. They observe that battery charging at stations is preferred during less busy periods of the day, while battery swapping becomes more advantageous during peak operational periods when rapid turnarounds are critical.

The paper integrates flight scheduling with charge scheduling while optimizing fleet composition to produce a feasible schedule from both a land and airside perspective. They also only considered a homogeneous fleet of AEA leaving room for a mixed fleet approach. The paper does not consider local electricity prices and does not allow for optimization on the level of network design, a gap this research aims to fill.

6.3.4. Comprehensive Approaches

In this section the most comprehensive approaches concerning electric aircraft and airline planning will be presented. The only difference between research here and in chapter 8 is that the latter will have papers that in addition also focus on fuel optimization. This section will present the research in order of least comprehensive to most comprehensive.

Westin et al. [75] developed an integrated airline planning model for Electric Aircraft in subsidized public service obligation (PSO) frameworks using a MILP. Their model optimizes network design, route frequency (such that the PSO minimum pax requirement is met), flight scheduling, and fleet assignment simultaneously from strategic to operational levels, using homogeneous 19-passenger, 400km-range electric aircraft. The paper does not include charge Siting, sizing, or scheduling, since it assumes charging is possible everywhere. Their two-layered network approach (aircraft operations and passenger flows) enables more flexible routing than traditional predetermined itineraries. Their comparison of different charging types found that fast-charging infrastructure (30 vs. 90 minutes) reduced fleet requirements by 40%, increased utilization from 22.7% to 23.2%, and decreased costs by 31%. Also, networks evolved from hub-and-spoke to multi-loop configurations with faster charging. This is relevant for this research since it shows the importance of fast charging and how AEA could benefit from unconventional network structures like a multi-loop.

Building on the integration of operational and strategic planning, Kinene and Birolini [13] developed an integrated optimization model that solves all critical air transport network design problems simultaneously: network design, route selection, route frequencies, fleet assignment, flight scheduling, charge Siting, charge sizing, and even charge scheduling. The model is called a three-dimensional Flight Scheduling and Fleet Assignment (3DFSFA) model, which employs a novel time-space-energy formulation to optimize the network design while balancing passenger surplus maximization and subsidy cost minimization. Their approach captures the complexities of electric aircraft operations by explicitly tracking energy consumption and charging requirements through a multi-commodity network flow formulation, while simultaneously accounting for passenger allocation to travel itineraries subject to aircraft capacity constraints.

Applied to a case study of Sweden's subsidized route network, their findings demonstrate that a hybrid fleet combining conventional and electric aircraft produces superior outcomes compared to homogeneous fleets (both fully electric or fully conventional), with 7 to 42% increases in passenger surplus and 22.3 to 42% reductions in well-to-wake greenhouse gas emissions under the same subsidy budget. A mixed fleet was found to significantly reduce needed subsidies because conventional aircraft provide faster speeds and larger seat capacities for efficient consolidation of passenger flows on a denser route, while electric aircraft offer lower operating costs, smaller size and reduced emissions, allowing higher frequency service, cost-effective operations on very thin routes, and more sustainable services. In particular, their analysis reveals that electric aircraft alone—despite their environmental benefits—lead to longer travel times (15.6% on average) and higher generalized travel costs (7.7% on average) due to their slower speed and limited range, highlighting the importance of strategically integrating different aircraft types to leverage their complementary strengths. This paper is especially relevant for this research since it shows the benefits of mixed fleets, something this research will also try to simulate, but while including dynamic electricity prices. The paper also does not consider varying or local electricity or fuel prices, instead having a fixed price for both across the entire network. This leaves room for this research to improve upon the groundwork laid by Kinene and Birolini.

6.4. Relevance for this research

The literature on EA operation within airline planning reveals a growing body of research addressing both landside and airside challenges. Landside studies have focused on infrastructure siting, sizing, and charge scheduling, often adapting EV frameworks to aviation contexts, as seen in works like [204] and [208]. Airside research has tackled network design, fleet assignment, and flight scheduling, with comprehensive approaches integrating multiple subproblems, such as [13] and [75]. However, despite these advances, several gaps remain that limit the applicability of existing models to real-world electric airline operations, particularly when considering dynamic operational constraints and economic factors. Below, we outline key research gaps and their relevance to this study on electric aircraft operation.

- **Limited Integration of Dynamic Electricity Prices:**
  Most existing studies, such as [219] and [13], rely on fixed or nonlocal electricity prices, disregarding the influence of regional price variations and time-of-use tariffs. This oversimplification overlooks opportunities for cost optimization through smart charging strategies tailored to local grid conditions. This research seeks to address this gap by incorporating dynamic, location-

specific electricity pricing into electric aircraft operational planning, thereby enhancing economic efficiency and grid compatibility.

- **Underdeveloped Mixed Fleet Optimization:**
  Although [218] and [13] investigate mixed fleets of conventional and electric aircraft, the full potential of such configurations remains underexplored. These studies demonstrate the benefits of subdividing routes between aircraft types based on static operational assumptions. However, they did not consider routes that switch between conventional and electric aircraft depending on the demand and costs of the route. For instance, mixed fleets could serve as a natural hedge against sudden spikes in recharging costs by reassigning conventional aircraft to high-cost routes. Such refleeting can be down quite late in the planning process allowing for the use of hopefully more accurate price forecasts. This research aims to develop a strategic model that captures part of this adaptive refleeting capability, unlocking new operational and economic advantages.

- **Inadequate Attention to Operational Flexibility:**
  While studies like [152] permit minor schedule adjustments to accommodate charging needs, broader operational flexibility remains largely unexamined. Designing routes and frequencies from the ground up, fully optimized for electric aircraft, could enable more strategic repositioning and adaptation to dynamic electricity prices. This approach would allow operational decisions, such as recharging schedules, to influence strategic planning stages, creating a more responsive and integrated airline operation framework. This research will explore such flexibility to bridge the gap between tactical adjustments and long-term planning.

These gaps highlight opportunities to advance electric aircraft operation research by addressing dynamic economic factors, operational integration, and scalability. This study aims to fill these gaps by developing a comprehensive model that optimizes airline planning for electric aircraft under realistic constraints, contributing to both academic understanding and practical implementation in the aviation industry.

7

Airline Planning & Energy Cost Management

Jet fuel has averaged 26% of airline operating costs since 2011 and in 2024 was 31% [109] and low-cost airlines often achieve even higher percentages [125]. In a bad year, as 2008, the costs of jet fuel rose to 50% of the operating costs [220]. It is by far the largest single expense for airlines, with depreciation and amortization at 9.1% and flight crew salaries and expenses at 8.6% being the runner-ups [221].

One way airlines handle high prices is by cutting back on flights, with 13% fewer domestic flights recorded in 2008 compared to 2007 [222]. Another, as shown by Gaye et al. [223] showed a direct correlation between increased fuel costs and increased airfare, negatively affecting passenger demand and profitability. The increase in ticket price caused by increased fuel costs can also be seen in Figure 7.1. This flow of fuel prices caused high airfares and subsequent drop in tourism traffic in 2008 according to the ICAO [224].

Due to its importance, much research has been conducted to optimize fuel expenditures. The industry has analyzed factors such as crude oil costs, jet fuel costs, price pressure in local markets, age of the fleet, fuel efficiency, and network design. Ryerson et al.[225] found that the price of fuel is a critical decision factor in fleet sizing. Given this, airlines need to optimize the strategic to operational aspects of their planning to increase the flexibility of their networks to greatly reduce fuel expenditures [220].

Since jet fuel costs have long been recognized as important, many of the papers in this section are more than 10 years old. This also makes it interesting for a study now to take these old ideas and repurpose them for modern AEA. The following section will present the relevant research in this area. Afterwards, the relevance of this research will be analyzed.

7.1. Relevant research

Given the significant impact of fuel costs on airline operations, research has evolved to address the multifaceted challenge of optimizing airline planning under volatile fuel prices. Early efforts focused on integrating core planning components (network design, fleet assignment, and frequency planning) to create robust networks capable of withstanding price fluctuations. Hsu et al. [220] developed a model that simultaneously tackles these three subproblems, assessing the reliability of the resulting network, defined as the probability that a route remains profitable or breaks even. To capture jet fuel price volatility, they employed segmented normal distributions derived from historical data, incorporating extreme scenarios triggered by global events.

Their findings highlight the vulnerability of routes with low load factors or long distances with high load factors during periods of abnormal price volatility. By identifying critical break-even load factors, airlines can adjust flight frequencies and aircraft types to minimize expected losses, a strategy that remains

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US industry correlation (6-month lag[1])

PRASM[2] YoY change, USD 2010-2016, percent

Jet fuel price YoY change (USD),[3] percent

Sample carrier 1 correlation (12-month lag[1])

PRASK[2] YoY change, USD 2010-2016, percent

Reported fuel cost YoY change (USD),[4] percent

Sample carrier 2 correlation (0-month lag[1])

PRASK[2] YoY change, USD 2010-2016, percent

Reported fuel cost YoY change (USD),[4] percent

[1]Time shift with the highest correlation between PRASM/PRASK and fuel costs chosen as the lag.
[2]Includes ancillary revenues.
[3]Based on average US. Gulf Coast kerosene-type jet fuel spot prices FOB (Dollars per gallon).
[4]Fuel cost per gallon calculated using reported quarterly total fuel cost and estimated quarterly fuel consumption (annual values adjusted using ASM to get quarterly consumption), does not include any gains/losses from hedge positions.
Source: US Department of Transportation, via Diio Mi; EIA; airline filings

Figure 7.1: Correlation between unit revenue and fuel costs for US industry and sample carriers indicates some degree of fuel cost pass-through [118]

highly relevant for electric aircraft, where recharge costs may exhibit similar volatility, necessitating network designs that can adapt to fluctuating energy prices.

Building on this foundation, Naumann et al. [125] extended the integration of operational and financial strategies by incorporating fuel hedging into a two-stage stochastic strategic planning model. Their approach determines optimal flight frequencies while accounting for uncertainty in both fuel prices and passenger demand, modeled through a matrix of scenarios combining five demand and ten fuel price variations. Robustness is evaluated using Conditional Value at Risk (CVaR) per route, revealing that higher fuel prices necessitate higher load factors to maintain profitability. The model also includes intermediate stopovers (ISOs) for itineraries with up to two stops and uses ticket price data to balance operational and hedging costs. Their results demonstrate that hedging can improve network robustness by 11.5%, despite a slight reduction in profits due to premiums, while dynamic integrated hedging yields 12.7% higher profits with equivalent robustness compared to static approaches. The concept of integrated hedging could be extended to electricity markets, where airlines might employ dynamic pricing contracts or energy storage solutions to mitigate cost uncertainties.

The challenge of uncertainty in fuel prices can also be modeled using stochastic modeling. Unlike [125], which models uncertainty by building a matrix of different possible scenarios, stochastic models use probabilistic data within their models. Techniques such as Sample Average Approximation (SAA) which uses sample averages across random scenarios to reduce the model size, produce fixed numbers to work with which help reduce the model size. However this technique is not deterministic since it changes every time the model is run.

Liu et al. [189] designed such a model by developing a risk-averse two-stage stochastic programming model for first fleet assignment and then aircraft routing, minimizing a weighted sum of expected value and CVaR to ensure both profitability and robustness. Their model leverages itinerary-based demand

and a time-space network for precise operational timing, assigning aircraft types to subnetwork layers. The results reveal a shift in priorities under high fuel price volatility: airlines favor smaller aircraft with lower absolute fuel consumption per kilometer over larger, more efficient-per-seat options, as the former mitigate risks of empty seats and cost exposure during demand fluctuations. These insights are crucial for electric aircraft fleet planning, where the choice between different aircraft types or battery configurations must balance energy efficiency with the risks posed by variable recharge costs and passenger demand.

Complementing these strategic models, smart operational tactics have emerged to further minimize fuel expenditures, such as stopping at airports just to refuel, or refueling more than needed at cheaper airports (fuel ferrying/ tankering). Leenawong et al. [226] tackled fuel cost optimization for long-haul flights requiring refueling stops, developing a MILP model with binary decision variables that optimize flight routes, aircraft types, refueling locations, and fuel quantities. By integrating fuel price variations across airports, their approach balances the cost of carrying additional fuel against savings from refueling at cheaper locations, enhancing cost efficiency within operational constraints. Similarly, Kheraie et al. [227] explored aircraft routing by incorporating fuel ferrying to exploit spatial price differences, proposing a MILP that integrates fuel management with fleet assignment and routing. Applied to a conceptual network, their results show that ferrying reduces total costs when prices vary between airports, despite the additional fuel consumption from carrying extra weight. For Electric Aircraft, this concept could translate into charging batteries beyond immediate needs at airports with cheaper electricity, trading off against increased turnaround times without the weight penalty inherent in fuel ferrying. Such operational tactics could be even more beneficial for electric aircraft, as strategic charging at low-cost airports could reduce costs without the weight penalty associated with fuel ferrying.

Together, these studies illustrate a progressive exploration of airline planning and fuel optimization, offering a robust foundation for adapting these approaches to electric aircraft.

7.2. Relevance for this research

The literature on airline planning and fuel optimization offers several key insights and methods that can be adapted to the context of electric aircraft recharge price optimization:

- **Stochastic Modeling of Price Uncertainty**: The use of stochastic programming to model fuel price volatility, as seen in [220] and [125], can be directly applied to electricity price fluctuations. By incorporating probabilistic models of electricity prices, airlines can design networks and schedules that are robust to recharge cost variations. This probabilistic statistical approach could be used instead of a retrospective approach using past electricity price data. It would make the model more applicable to assess future networks but could provide less accurate analytical insights when compared to actual price data.

- **Integrated Financial and Operational Strategies**: Hedging strategies for fuel, as explored in [125], inspire similar approaches for electricity procurement. Airlines could use financial instruments or dynamic pricing contracts to mitigate the risks associated with volatile electricity prices, enhancing the robustness of their operations.

- **Fleet Composition under Uncertainty**: The findings from [189] on fleet assignment under fuel price and demand uncertainty can inform decisions about electric aircraft types and battery configurations. Airlines may prefer aircraft with lower absolute energy consumption or flexible battery sizes to adapt to varying recharge costs and passenger demand. The paper also shows how a mixed fleet assignment problem can be solved by creating a network sub-layer for each aircraft type and then combining the results.

- **Operational Tactics for Cost Minimization**: Strategies like fuel ferrying, as discussed in [227], can be reimagined for electric aircraft. By strategically charging at airports with lower electricity prices, airlines can reduce overall recharge costs, trading off against increased turnaround times. In particular, unlike fuel, electricity storage does not incur a weight penalty, which makes this strategy even more advantageous. The challenge will be to see how such operational tactics can be incorporated into a strategic model.

- **Network Design and Route Profitability**: The methods for assessing route reliability and break-even load factors in [220] can be adapted to evaluate the profitability of routes for electric aircraft, considering both recharge costs and passenger demand. Such methods include reliability as a measure of probability that the route remains profitable and metrics like CVaR. This can help airlines identify and adjust vulnerable routes in their network.

- **Localized Fuel Price Variations:** Again, existing studies often overlook spatial variations in fuel prices between different airports or regions. For electric aircraft, electricity prices can vary widely due to local energy markets and infrastructure, making it essential to incorporate these differences into recharge price optimization models to achieve more accurate and effective cost management.

These adaptations highlight the potential for transferring established optimization techniques from traditional fuel-based aviation to the emerging field of electric aircraft, ensuring economic viability in a sustainable aviation future.

8
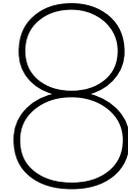
Intersection of All Three Research Fields

This chapter presents the most relevant research for this study, focusing the final intersection of the Venn diagram (Figure 1.1). It will elaborate on research about airline planning with electric aircraft and fuel optimization, specifically recharge optimization in this context. The research in this area is limited, with only a few papers covering all aspects, but it is current, as seen in their publication dates: 2019, 2022, 2023 twice, and 2024. The papers will also be discussed in this chronological order. While some work exists, gaps remain, and addressing them could add value to the field.

8.1. Most relevant academic research to date

Unlike earlier chapters, which built a cohesive story of the research area, this one analyzes each paper individually before offering a synthesis. This structure allows for a deeper examination of each study which is needed in this final phase of the literature study.

8.1.1. Pereira (2019) (TU Delft): Short-range route scheduling for electric aircraft With battery-charging and battery-swapping constraints

Pereira [78] formulated a two-stage MILP model to optimize EA operations for 49 short-range flights (up to 350 km) from Amsterdam Airport Schiphol. The model focuses on *fleet assignment*, *flight scheduling*, *charge siting*, *charge sizing*, and *charge scheduling*, but excludes *network design*, *route selection*, and *frequency planning* due to a predefined mission set. It integrates battery swapping and charging within a two-stage framework: the first stage assigns a homogeneous EA fleet to round-trip missions with fixed times while ensuring sufficient SOC in the batteries; the second stage refines this into a minute-by-minute schedule, minimizing charging stations and spare batteries. Charging is modeled using a bilinear function of initial and final SOC, with full charging taking up to 4.6 hours, though partial charging suffices for the next mission plus a 20% safety margin. Energy needs are estimated using the EA adapted Breguet formula (Equation 2.2).

A fixed electricity price of 0.083 €/kWh is applied uniformly across the network (note: 2024 EU average electricity price is 0.2560 €/kWh (a 308% increase)[155]). Therefore the model does not consider varying or local electricity prices. No sensitivity analysis on electricity prices is included, though future work suggests exploring dynamic pricing effects on schedules, costs, and profits.

The papers results could be interesting for this research to compare to in a later phase. Case study results indicate 15 AEA are needed compared to 14 conventional aircraft, attributed to

longer charging times versus refueling. Will the comparison of conventional and AEA in this research show the same effect? Also, sensitivity analysis shows that reducing airborne hours from 13.33 to 7 increases fleet size to 23 and costs by 56% to €3.23 million, while reducing swaps by 78.8% to 2. What would it look like if the airborne hours could be increased for AEA, allowing them to operate for 1 hour longer at night due to a quieter noise profile? Other results showed that lowering charging power increases swaps to 17, spare batteries to 11, and costs by 10% to €2.28 million, with fleet size unchanged at 15. What would the effects of slower charging be on this research model? Maybe the network will prioritize cheaper recharging even more and shift the network accordingly.

This is a TU Delft master thesis with supervisors Prof. Mihaela Mitici, and Prof. Fabrizio Olivero.

8.1.2. Justin et al (2022) (Georgia Institute of Technology): Integrated fleet assignment and scheduling for environmentally friendly electrified regional air mobility

Justin et al. [73] optimized regional air mobility (RAM) using electric and hybrid-electric aircraft through a half-leg half-itinerary MILP with a hierarchical multi-objective approach, maximizing profits and minimizing carbon emissions. This paper addresses *network design* (hub-and-spoke vs. point-to-point), *route selection* (market and itinerary generation), *route frequencies* (flight frequency optimization), *fleet assignment* (aircraft allocation), and *flight scheduling* (departure/arrival timing), but not *charge siting*, *charge sizing*, or *charge scheduling*, though battery technology impacts are analyzed.

The methodology estimates demand from mode choice models and travel data, distributed across daily time periods (flexible, multi-hour blocks, not strictly hourly). These demand profiles are then fed into the model along with inputs such as operating costs and emissions (fuel and electricity) to output fleet size, routes, and schedules. It operates strategically, determining flights per leg per period without detailed per-aircraft schedules, ensuring feasibility via aircraft conservation and overnighting constraints, balancing flows across periods and airports.

A sensitivity analysis on battery technology (275 to 450 Wh/kg) showed that a higher battery density boosts profits (+15.8%) and fleet size (+7.5%), reducing emissions (-46.6% per passenger-mile). It shows the important of battery energy density in AEA operations. These sensitivity tests can be replicated by this research to observe if the same effects if found.

Another analysis on network topology impacts (hub-and-spoke vs. point-to-point) showed how point-to-point networks cut costs (-28.4%) and emissions (-28.3%) but serve fewer markets (-45.8%) and passengers (-24.5%). This is relevant for this research since this research will include a network design phase where a decision of network topology will have to be made.

Concerning the mixed fleet and electricity price characteristics of this paper: the fleet used is a semi-mixed fleet comprising only electric (9 passenger) and hybrid electric (19 and 48 pax) aircraft, excluding conventional fuel-powered models. Recharging electricity prices are standardized across the network based on averages, without local or temporal variation. This also excludes the possibility of electricity ferrying. Partial recharging is not modeled with aircraft are assumed fully charged to meet leg requirements (distance plus reserves). All of these aspects could be improved upon.

Personal Note
This paper is the most advanced paper found that is relevant for this research. It covers all relevant airline planning subproblems and even does very in-depth demand modeling. It almost seems suspicious that the only thing the paper did not do was modeling local and varying electricity prices. I will try to get into contact with the author to ask this question and more.

8.1.3. Vehlhaber and Salazar (2023) (IEEE / TU Eindhoven): Electric Aircraft Assignment, Routing, and Charge Scheduling Considering the Availability of Renewable Energy

Vehlhaber and Salazar [69] (not to be confused with their 2024 paper) present a novel optimization framework for the assignment, routing, and charge scheduling of Electric Aircraft that explicitly accounts for the availability of renewable energy in airports. The authors formulate a mixed-integer linear program that captures the intricate coupling between airside operations and landside energy management by modeling aircraft movements within a time-space directed acyclic graph while simultaneously tackling the dynamic local energy production of individual airports equipped with renewable energy sources and stationary batteries. Their approach minimizes grid dependency by strategically scheduling flights to align with peak renewable energy generation periods, resulting in a reduction in grid dependency by 18-100% compared to conventional schedules, depending on weather conditions.

Through minimizing grid dependency, the paper indirectly incorporated local electricity prices into its model under the assumption that renewable energy produced locally will be cheaper than grid electricity. It also models varying electricity prices indirectly since it the amount of renewable energy changes over time. This model could be adapted to include actual grid prices.

8.1.4. Van Amstel (2023) (TU Delft): Optimizing the Energy and Charging Infrastructure Costs for Regional Electric Aircraft Operations

Van Amstel [27] proposes a MILP model to minimize total energy and charging infrastructure costs for AEA operations at Bonaire International Airport (BIA) flying inter-island (maximum 200 km) to Curaçao and Aruba. The daily operational model allows flight schedule flexibility (±30 min shifts, 10-min intervals), while the yearly energy model balances renewables and grid use, both optimizing costs of energy provision (solar panels, wind turbines, battery storage), charging stations, and operations (battery lifetime, time shifts, repositions). Electricity prices are fixed and network-wide the same, proving a research gap to fill. The model does include a 0.01 USD/kWh return fee which is revenue for surplus energy fed back into the grid.

The fleet may consist of a 9-seaters (Eviation Alice) or 19-seaters (Heart ES-19) with no conventional aircraft considered. The energy needs are estimated through the electrified Breguet (Equation 2.2). The daily model schedules charging per aircraft with short time intervals and allows partial recharges. It models both fast and slow charging as well as their respective effects on battery health. Fast charging caused more battery degradation and also increased utilization thereby deteriorating battery health even faster. The key finding of the report was that allowing 30 min schedule flexibility cuts daily costs by up to 50%.

Uniquely, the study integrates renewable energy with flexible scheduling, contrasting fixed-schedule models. It addresses *fleet assignment*, *flight scheduling*, *charge sizing*, and *charge scheduling*, but not *network design*, *charge Siting* (all airports are electrified), *route selection*, or *frequency planning*, given the fixed route set. The research thus models EA operations from a landside / airport perspective leaving room for an air side / airline perspective.

This is a TU Delft master paper with supervisor Dr. B.F. Lopes Dos Santos, Ir. P.C. Roling, Ir C.L.V. Driesen (company supervisor), and Dr. C. Varriale.

8.1.5. Vehlhaber and Salazar (2024) (TU Eindhoven): A Model Predictive Control Scheme for Flight Scheduling and Energy Management of Electric Aviation Networks

Vehlhaber and Salazar propose a novel Model Predictive Control (MPC) scheme for dynamic flight scheduling and energy management in electric aviation networks, addressing the challenge of minimizing grid dependency by leveraging renewable energy and battery storage at airports [142]. The model integrates aircraft flight and charge scheduling with airport energy

management, using a time-extended directed acyclic graph to capture the time-varying nature of the network and incorporating weather forecasts to handle renewable energy uncertainty. By solving a MILP in a receding horizon framework, the approach optimizes aircraft assignments and energy usage to balance grid power consumption and flight delays. Simulations on a real-world commuter flight network in the Dutch ABC-Islands illustrate the scheme's effectiveness in adapting to operational disruptions and variable energy conditions, enhancing the resilience and sustainability of electric aviation operations.

The paper tackles the problems of *Fleet Assignment*, *Flight Scheduling* (with schedules that adapt to delays and energy needs within a receding-horizon approach), and *Charge Scheduling*, but since it uses a given network and schedule it does not address *Network Design*, *Route Frequencies*, *Charge Siting* (all airports electrified), or *Charge Sizing*. By using a fixed network design, the model is not allowed to optimize the network topology on where renewable energy will be produced and when. This, but for grid power, will be a focus of this research.

The paper mentions that future work will add demand response from the local grid to the framework. Due to the large powers required for charging electric aircraft quickly for fast turnaround times, dynamic grid response will likely be a factor for future airports and airlines to consider.

8.2. Research Gap

The previous chapters reviewed electric aircraft (Chapter 2), fuel optimization (Chapter 3), and aircraft planning (Chapter 5), along with their intersections (Chapters 4, 7, 6). This chapter has tackled the inner triple intersection of the Venn diagram thereby finish the exploration of all parts of these combined research fields (Figure 8.1).
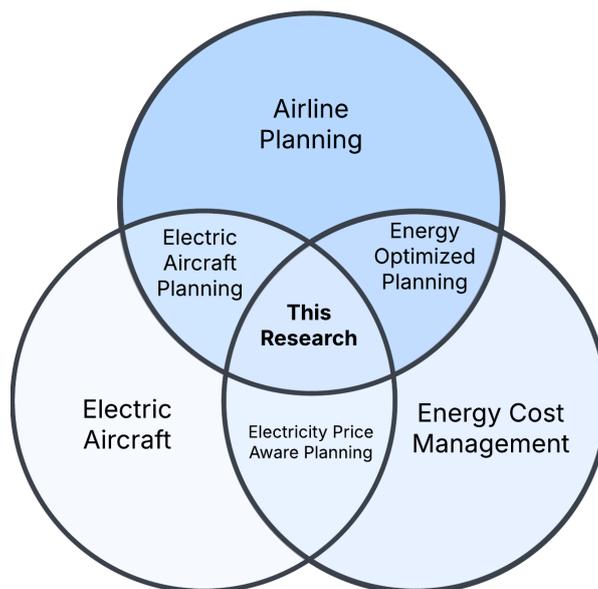
Figure 8.1: Venn diagram showing the 3 key intersecting research fields

Prior chapters explored the benefits of electric aircraft, such as lower fuel costs, and constraints, such as limited range, while analyzing fuel cost strategies and planning processes. The literature review examined numerous papers across these topics. To sharpen the focus on the research gap, the table on the next page summarizes all relevant studies, with key columns highlighting airline planning problems, model fidelity, and fleet type. The table reveals that existing research addresses various aspects of these dimensions.

The final two rows of the table present two proposed models for this research, each tackling a unique combination of these columns not yet addressed in the literature. The remainder of this section explains

why this combination merits investigation. The first model, a deterministic approach, uses historical electricity prices by location and historical demand to optimize network design, route frequency, and fleet assignment, incorporating dynamic electricity costs. This model offers insights into network stability, route reliability, and the profitability of an electric flight network if implemented and optimized today. The second model extends this by addressing real-world uncertainty, where future electricity prices and demand are unknown and must be forecast. As departure dates approach, forecasts improve, but planning decisions must already be underway. Thus, this model iteratively replans the network, route frequencies, and fleet assignments as better forecasts emerge, while respecting fixed planning timelines for each step. This research will prioritize the first model, as it forms the foundation for the second, providing a core framework for further development.

Year	Author	Airline Planning Problem				Method	Model Fidelity			Uncertainty		Aircraft		
		Network Design	Route Frequency	Fleet Assign.	Flight Scheduling		Local Fuel Costs	Varying Fuel Costs	Varying Demand	Uncertain Fuel	Uncertain Demand	Fleet Type	Range	Charge Siting
2024	C. Leenawong et al	✓		✓		MILP (binary)	✓					Conv.	Long	
2024	F. Vehlhaber et al					MPC, MILP (receding horizon)	✓	✓				Elect.	Short	All
2024	A. Kinene et al	✓	✓	✓	✓	MILP			✓			Mixed	Short	Optimized
2024	J. Westin et al	✓	✓		✓	MILP (network flow model)						Elect.	Very Short	All
2023	T. de Jesus et al		✓	✓		MILP						Conv.	Medium	
2023	P. Proesmans et al		✓	✓	✓	DP			✓			Conv.**	Long	
2023	B. Chan et al			✓		MILP (time-space network)						Mixed***	Short	
2023	M.Liu et al			✓		MILP (two-stage)		✓	✓	✓	✓	Conv.	Long	
2023	A. Kinene et al	✓				MILP, KS Heuristic						Elect.	Short	Optimized
2023	F. Vehlhaber et al			✓	✓	MILP (time-space network)	✓*	✓				Elect.	Very Short	All
2022	C. Justin et al	✓	✓	✓	✓	MILP			✓			Mixed*	Short	All
2022	M. Faa	✓				-						Mixed	Short	Optimized
2022	M. Mitici et al				✓	MILP (two-phase)			✓			Elect.	Very Short	Hubs only
2021	V. Özkır et al			✓	✓	Heuristic (two-phase), Integer Programming						Conv.	Medium	
2021	A. Ham et al				✓	MIP, CP		✓				EV Cars	Very Short	
2021	V. Özkır et al	✓		✓		MILP (two-phase) & Heuristic (two-phase)						Conv.	-	
2020	C. Justin et al					Linear Programming (Network Flow Model)	✓					Elect.	Very Short	All
2019	M. Pereira et al				✓	MILP (two-stage)						Both	Very Short	All
2013	C. Hsu et al		✓	✓		MILP		✓	✓	✓		Conv.	Long	
2013	M. Naumann et al	✓	✓			MILP (two-stage)			✓	✓	✓	Conv.	Long	
2013	C. Hsu et al			✓		MILP		✓	✓	✓		Conv.	Long	
2012	A. Kheraie et al	✓		✓	✓	MILP (flight string)	✓					Conv.	Short	
2012	M. Naumann et al		✓	✓		MILP (two-stage)		✓	✓	✓	✓	Conv.	Long	
2002	C. Hsu et al		✓			NLP			✓		✓	Conv.	Long	
	Deterministic Analysis Model	✓	✓	✓		MILP (2-stage / integrated)	✓	✓	✓			Mixed	Short (E9X)	All
	Continuous Improvement Model	✓	✓	✓		MILP, two-phase heuristic	✓	✓	✓	✓	✓	Mixed	Short (E9X)	All

*Account for local electricity production
  but not local grid prices

* Mixed Conv., Hybrid, and Electric

** Climate optimized design

*** Mixed Conv. And Hybrid only

Both = Only Elect. vs. Only Conv.

Mixed = Conv & Electric

Electric aircraft promise cost savings due to cheaper electricity compared to jet fuel. However, real operational costs depend on electricity prices, which could reflect the 30% share jet fuel is of expenses in conventional aviation. Without models that account for price variations, the economic viability of electric aircraft remains unclear, driving the need for this research. The following key gaps emerge from the literature:

1. **Local electricity prices not considered in network design**

   Electricity prices vary by location, unlike jet fuel prices, which remain relatively stable over short distances. Most research on electric aircraft assumes a uniform, network-wide electricity price. For example, studies on jet fuel tankering optimize refueling quantities within fixed schedules but do not adjust routes based on price differences. For electric aircraft, where prices can differ significantly even across small regions, local variations could determine which routes are most profitable. Current models emphasize refueling or recharging optimization in static networks, neglecting how spatial price disparities could reshape network design and topology from the ground up. While jet fuel price differences have minimal impact on short-range flights, electricity price locality could influence even small networks, a factor overlooked in existing studies.

2. **Varying electricity prices over time not modeled**

   Electricity prices fluctuate over time and can be highly volatile, with prices potentially dropping in one country while rising in another. In contrast, jet fuel prices tend to move more uniformly across vast regions. These shifts continuously alter the balance between demand and costs for each route, yet no research has explored the extent of this impact. Current models fail to capture how time-varying electricity prices could affect operational planning, leaving a gap in understanding their influence on route profitability and network dynamics.

3. **Full potential of mixed fleets underexplored**

   Mixed fleets combining conventional and electric aircraft are examined for assigning fixed routes based on range and capacity, not for reassigning routes as electricity costs change. Instead of having one route assigned to one aircraft type, routes could switch between aircraft types (conventional or electric) if the electricity and jet fuel prices at the recharge / refuel location justify it. Exploring how often this would happen in the real world has not been done yet. Current research misses this chance to adapt operations to shifting economic conditions, limiting the potential of mixed fleets.

4. **Longer electric aircraft ranges not addressed**

   Most studies target electric aircraft with ranges under 500 km, reflecting the first models entering the market. No research was found exploring ranges of 800-1000 km, such as those targeted by the E9X. Longer routes could increase flight time and likely charging time, potentially affecting utilization and profits. For instance, overnight charging might offset downtime, raising utilization, but existing models do not account for these dynamics. This leaves a gap in planning for next-generation electric aircraft designed for greater reach.

5. **Little focus on strategic-level planning**

   Range is often included in strategic planning models for electric aircraft, but factors like recharging costs, recharging time, and battery health are typically addressed only in tactical and operational models, such as flight and charge scheduling. Integrating these operational factors into strategic decisions—such as network topology, flight frequency, and mixed fleet assignment —could yield more optimized and comprehensive models aligned with the needs of electric aircraft. Since electricity prices are likely a major operating cost, dynamically adjusting the network to reflect these costs could improve profits. While static networks offer logistical simplicity and customer loyalty, without modeling a dynamic alternative, the trade-offs in cost savings and flexibility remain unclear. Comparing static and dynamic approaches could reveal what is sacrificed by prioritizing stability over adaptability. Therefore allowing factors such as recharging costs, time, battery

health to influence the entire network from top to bottom could show interesting interactions.

Research Gap Statement:
This study identifies the need for a planning framework that integrates electricity price variations into a strategic planning model for Electric Aircraft. Current research lacks models that address local and time-varying electricity prices, dynamic mixed fleet optimization, longer ranges like the E9X's 800-1000 km, and allow these effects to reshape the entire network. In partnership with Elysian Aerospace, this research aims to develop such a framework, leveraging the capabilities of E9X to improve efficiency and competitiveness.

9

Research Proposal

Aviation is traditionally a thin-margin sector where operational efficiency is critical to profitability. As the industry transitions toward electric aircraft, electricity costs will become a significant portion of operating expenses, largely driven by spatiotemporally volatile prices. This creates an opportunity to optimize profitability by aligning flight operations and, specifically, charging strategies with favorable electricity prices. A model that incorporates these factors requires a fundamental expansion of traditional strategic planning. Therefore, the question is whether it is worth incorporating local and varying electricity prices into the optimization model and what strategic behaviors emerge from doing so. This leads to the research objective:

> **Research Objective:**
> This study aims to better align conventional airline planning models with electric aircraft by incorporating high-resolution cost data and expanding the set of strategic planning problems considered.

9.1. Research Questions

> **Central Research Question:**
> To what extent does the inclusion of strategic charge decisions, mixed-fleet assignment, and spatiotemporal electricity prices in a strategic planning model for electric aircraft enhance its performance, measured from both a financial and structural perspective?

To support finding the answer to the research question, three refined sub-research questions are defined:

> **Sub-Research Questions**
>
> 1. **Strategies under Spatiotemporal Pricing:** What optimal planning strategies and structural decisions are revealed by an expanded electrified aviation network model that incorporates spatiotemporal electricity prices?
>
> 2. **Planning Value:** What is the financial value of incorporating different granularities of electricity price information into strategic airline planning models for electrified aviation?
>
> 3. **Mixed Fleet Strategies:** How does the strategic composition and dynamic reassignment potential of a mixed fleet (electric and kerosene aircraft) influence overall network profitability, financial stability, and operational specialization in response to fluctuating energy prices?

Explanation of Research Sub Questions:
Sub-research question 1 investigates the core focus of the study by examining how spatiotemporal variations in electricity prices affect strategic decisions. Unlike traditional planning, which assumes fixed fuel costs, this question seeks to uncover novel behaviors such as "charge ferrying" (carrying extra energy to avoid expensive airports) and "charge siting" (optimizing where to charge). It analyzes how the network structure (route selection and frequency) changes when the model is given the freedom to optimize based on accurate price dynamics.

Sub-research question 2 quantifies the "Value of Knowledge." It assesses the economic penalty of relying on simplified price assumptions, such as fixed annual averages or uniform regional prices, which is common in existing literature. By comparing a perfect-information model against models with imperfect or averaged price data, this question isolates the specific value of price awareness, price magnitude accuracy, and temporal granularity (e.g., monthly vs. annual data).

Sub-research question 3 explores the integration of a mixed fleet comprising both kerosene and all-electric aircraft. It addresses how the network can leverage the complementary strengths of both aircraft types: using electric aircraft for arbitrage in stable, low-cost electricity markets, and switching to kerosene aircraft during periods of high electricity price volatility (e.g., the 2022 energy crisis). This question evaluates the "natural hedge" provided by a mixed fleet and determines the optimal fleet composition to balance risk and return.

9.2. Research Scope and Assumptions
To focus the research on the research question, extensive scoping and assumptions have to be set in place in order to contain model complexity and minimize the effect of confounding variables. The following list lists the main assumptions and limitations.

- **Time Scope:** This study focuses on strategic and tactical airline planning, targeting long-term trends rather than short-term operational dynamics. Daily mean electricity prices will be used to capture spatiotemporal variations, avoiding hourly fluctuations that align with operational scheduling problems already addressed in the literature.

- **Demand Variation:** Passenger demand variations will be incorporated to balance against fluctuating electricity prices. Seasonal trends, such as high summer demand and corresponding electricity price shifts, will be modeled to evaluate trade-offs between costs (electricity prices) and revenue (passenger demand).

- **Uniform Fleet:** The analysis will assume a fleet composed of a single electric aircraft type, such as the E9X, to isolate the effects of electricity price variations. A varied fleet (e.g., varied electric or conventional kerosene aircraft) would introduce confounding synergy effects on KPIs diluting the focus of the research.

- **Reference Kerosene Aircraft:** A turboprop kerosene aircraft, comparable to electric aircraft like the E9X in operational use, will serve as the reference. Two or three similar kerosene aircraft will be selected and tested individually in the sensitivity analysis. Ideally, a reference aircraft would be chosen based on acquisition cost to fully leverage the benefits of kerosene's increased energy density, but this is highly unlikely due to unreliable E9X price predictions.

- **Technology Timeline:** The reference kerosene aircraft will be technologically scaled to 2035, aligning with the E9X's introduction year. This ensures a fair comparison by extrapolating slight improvements to existing kerosene aircraft, reflecting their typical lifespan exceeding 10 years.

- **Fuel Choice for Reference Aircraft:** Fully kerosene-powered aircraft will be used as the baseline, excluding SAF. SAF's variable incorporation (up to 50% in jet fuel) introduces additional complexity, and its limited current use (less than 0.2% of fuel consumption in 2024). SAF effects may be explored in sensitivity analysis.

- **Airport Selection:** Only major European hub airports will be considered, as they possess the demand and infrastructure (e.g., significant power capacity) to support large electric aircraft like the E9X. Future expansions could include a broader set of suitable airports, potentially using hierarchical clustering to manage computational complexity.

- **Charge Siting:** All selected hub airports will be assumed fully electrified. Electrifying an airport is costly and slow and thus falls outside the scope of strategic and tactical fast replanning influenced by electricity prices.

- **Electricity Source:** The study will assume grid-dependent electricity rather than locally produced power (e.g., on-site renewables). While grid independence is appealing, future electrified airports are likely to rely heavily on grid power, aligning with realistic infrastructure expectations.

- **Electricity Production Method:** This research will focus solely on electricity prices, not production methods (e.g., green energy optimization) to maintain focus on spatiotemporal price impacts. Increased regional production, for example, from renewable sources, is often reflected in the price.

- **Charger Type:** Plug-in charging will be modeled, consistent with the E9X's design, ensuring compatibility with the selected electric aircraft type.

- **Charge Power:** A single charge power will be assumed, as varying charge power per charger has been explored in prior literature. Sensitivity analysis may later assess its influence if relevant to strategic outcomes.

- **Charging Time:** A bilinear charge curve will estimate charging duration based on the state of charge (SOC) required, reflecting realistic battery behavior for electric aircraft operations.

- **Partial Recharging:** Dynamic charging times will be incorporated, tailoring SOC to the needs of each flight leg. While the base model assumes charging per leg, future expansions may explore non-charging intermediate stopovers, though this risks over complicating the model.

- **Intermediate Stopovers:** The base model will not model transfer passengers explicitly in order not to overcomplicate the model.

- **Charge Ferrying:** Transporting cheaper electricity via aircraft (charge ferrying) will not be initially included due to its operational complexity. It may be added later if a suitable strategic constraint can be formulated. This will also benefit kerosene aircraft.

- **Maximum Chargers per Airport:** The number of chargers will remain unlimited and unmodeled, as detailed aircraft routing (needed to estimate simultaneous aircraft presence) is beyond this study's scope.

9.3. Methodology

To answer the research questions a strategic airline planning model will be built that can use spatial and temporal electricity data. This model will be tested on a case study in order to produce results that will then be analyzed so that the research questions can be answered.

The research will use a case study to test the devised model. The case study will be a regional market in Western Europe. Europe was chosen because 1) the national borders cause electricity prices to differ more greatly over distance, 2) it is a likely entry market for Elysians E9X, and 3) data is more readily available through Eurostat.

The model will be developed in Python and will utilize a MILP architecture. MILP was selected because it is the most commonly used approach in the literature, enabling the integration of constraints from various models to construct this one. Additionally, MILP is an optimal solver, which makes it well suited for this purpose. While alternative sub-optimal methods are preferred to reduce computation time, this research does not involve an extremely large number of nodes nor is it intended for operational use. Instead, it focuses on analysis and review, making MILP the most appropriate choice. A potential challenge with MILP is that the problem could become non-linear, but this risk can be mitigated with careful design. Another potential challenge is that the number of iterations needed to simulate each time step may take too much computational time. If this is so, then alternative methods will have to be explored, but even so, the MILP will be needed as a benchmark for smaller test instances.

The core MILP will be a network design and frequency planning MILP adjusted for electric aircraft and expanded to include local electricity prices. This model will then be upgraded to include mixed fleet assignment. The resulting model will then serve as the core of the temporal model that will iterate this model for the different time steps. After the core functionalities of the model have been achieved, work on more refined inputs such as better demand data can help improve the model.

9.4. Project Planning

In this section, the research planning will be presented. This will first be done by presenting the key dates in Table 9.1. The project has been broken down into 6 workpackages which are described in Table 9.2.

9.4.1. Important Dates

Table 9.1: Thesis Schedule

Name	Date	Work Week	True Week	Vacation Days
Vacation	Mon 28 Apr – Fri 2 May		12	5
Midterm Deadline	Thu 19 Jun	18	19	
Midterm Review	Thu 26 Jun	19	20	
Recovery	Mon 30 Jun – Fri 25 Jul		21–24	20
Potential Vacation	Wed 30 Jul – Fri 1 Aug	20	25	3
Vacation	Mon 11 Aug – Tue 26 Aug		27–29	12
Vacation	Fri 3 Oct	27	34	1
Draft Deadline	Fri 14 Nov	33	40	
Green Light Review	Fri 21 Nov	34	41	
Final Hand-in	Fri 12 Dec	37	44	
Thesis Defense	Fri 19 Dec	38	45	
			Total:	21

Work weeks and true weeks both start on February 10th, 2025, at week 1. The maximum allowed date for the thesis defense is work week 40, true week 51 (calculated as 40 work weeks + 7 vacation weeks + 4 weeks for a granted extension), corresponding to January 30th, 2026. The objective is to complete the master's degree in 2025. The schedule accounts for a planned 4-week leave of absence between June and July. Consequently, the thesis defense is planned for December 19th, 2025, which corresponds

to work week 38 and true week 45. This timeline utilizes only 4 vacation weeks, effectively increasing the work rate to meet the 2025 deadline. While a 4-week extension has been formally approved as a contingency, the aim is to finish before the end of the year to avoid logistical challenges associated with the Christmas holiday period.

9.4.2. Work Package Breakdown
The work package breakdown is shown in Table 9.2.

WP	WP Name	Task Title	Description
0	**Literature Review & Proposal**		
0.1		Literature Review	Draft Finished
0.2		Research Proposal	Draft Finished
1	**Data Accumulation**		
1.1		Identify Available Data	Document data constraints (e.g., availability, granularity) related to electricity prices, jet fuel prices, and airline operational data.
1.2		Collect Price Data	Acquire spatiotemporal electricity and jet fuel price data for model inputs, ensuring relevance to real-world conditions.
1.3		Compile Operations Data	Gather airline operational data (e.g., routes, frequencies, fleet composition) to establish a realistic optimization baseline.
1.4		Process Data	Process the data such that it can be used by the models.
2	**Base Model**		
2.1		Build Planning Model	Develop the base strategic planning model for network design and route frequencies.
2.2		Incorporate Price Data	Implement functionality in the model to process spatiotemporal electricity price variations for optimization purposes.
2.3		Add Kerosene Baseline	Incorporate a kerosene-powered fleet into the model to enable profitability and stability comparisons.
2.4		Add Stability Metrics	Integrate stability metrics (e.g., route and frequency changes) to evaluate network stability over a one-year period.
2.5		Verify Model	Verify base model correct functionality using sample data to ensure accuracy and optimization efficiency.
2.6		Preliminary Results	Assess the profitability and stability of the all-electric fleet with and without price variations, compared to the kerosene fleet. Rough results can be used as a progress check and sanity.
3	**Expanded Model**		
3.1		Add Mixed Fleet	Extend the model to incorporate mixed fleet assignment (kerosene and electric) with dynamic assignment capabilities.
3.2		Dynamic Reassignment	Develop algorithms for continuous fleet reassignment based on real-time price fluctuations.
3.3		Validate Model	Verify the expanded model's accuracy in dynamic fleet assignment under varying price conditions.
3.4		Mixed-Fleet Prelim. Results	Evaluate profitability and stability outcomes for the mixed-fleet model with dynamic reassignment.
4	**Improvement Phase**		
4.1		Simulate Constraints	Simulate real-world constraints (e.g., limits on frequency or magnitude of planning adjustments) within the model.
4.2		Enhance Demand Data	Develop and incorporate more realistic demand data.
4.3		Validate Model	Test the improved model to confirm correct implementation of constraints and computational efficiency.
4.4		Improved Results	Analyze trade-offs between profitability, stability, and computation time under constrained conditions.
5	**Analysis Phase**		
5.1		Final Results	Calculate final results across all models
5.2		Scenario Analysis	Evaluate network performance under various scenarios (e.g., price volatility, fleet composition).
5.3		Sensitivity Analysis	Investigate the impact of key parameters (e.g., price variability) on model outcomes.
5.4		Synthesize Findings	Summarize key insights regarding spatiotemporal variations, mixed fleets, and constrained planning approaches.
6	**Thesis Writing**		
6.1		Draft Thesis	Compose a thesis draft including introduction, literature review, methodology, results, and discussion sections.
6.2		Green-Light Review	Prepare presentation materials and a draft for the green-light review to obtain feedback.
6.3		Finalize Thesis	Revise the thesis based on feedback, finalize the document, and prepare for the defense.

Table 9.2: Work Package Descriptions with Tasks

10
Conclusion

The aviation industry faces significant pressure to improve environmental sustainability, driving interest in novel propulsion systems such as AEA. While AEA offer potential benefits such as zero direct emissions, reduced noise, and potentially lower maintenance costs, their operational viability and economic feasibility, particularly concerning energy costs, remain critical areas of investigation needing further research.

This report provides a comprehensive literature review spanning electric aircraft technology, fuel optimization principles, and aircraft planning methodologies, exploring their individual characteristics and their intersections. The review highlighted the distinct nature of electricity pricing seen through its inherent spatiotemporal volatility and localization. The report also highlighted the factors that cause this behavior, such as grid constraints, renewable energy penetration, varying demand, and taxation policies, and showed how this contrasts with the more globally correlated, though still volatile, nature of jet fuel prices. Existing research has examined many parts of AEA operations, such as infrastructure siting and sizing, charge scheduling, and integrated planning for shorter-range EA.

However, a significant gap persists in the literature, as identified in chapter 8. There is a lack of strategic airline planning models that fully uses spatiotemporal electricity costs and allow these costs to influence fundamental network decisions such as route selection, frequency planning, and fleet assignment, especially for longer-range electric aircraft like the Elysian E9X. Furthermore, the potential for adaptive strategies, such as dynamically reassigning routes between conventional and electric aircraft in a mixed fleet based on fluctuating energy prices, remains largely underexplored at the strategic level.

To address this gap, the primary objective of the proposed research is to evaluate the benefits and opportunities of accurately incorporating the operational costs of electricity in the strategic planning of all-electric aircraft. This objective is encapsulated in the central research question: *To what extent does the inclusion of strategic charge decisions, mixed-fleet assignment, and spatiotemporal electricity prices in a strategic planning model for electric aircraft enhance its performance, measured from both a financial and structural perspective?* Supporting subquestions will further investigate the impact on profitability and network stability for both uniform all-electric and mixed fleets, and analyze the trade-offs associated with imposing realistic limits on planning adjustments.

The proposed research methodology involves developing a strategic airline planning optimization model designed to handle spatiotemporal electricity price data and passenger demand variations. This model will be applied to a European case study, simulating various scenarios (including different pricing assumptions, demand levels, and fleet compositions) to quantify the effects of electricity price dynamics. The research stands out by being the first to incorporate and assess the benefits of the following key contributions.

1. Local electricity prices that differ by origin and destination.
2. Electricity prices that fluctuate over time.
3. Dynamic reassignment of a mixed fleet.
4. Electric aircraft with a longer range than those considered in existing studies.

By systematically evaluating the impact of realistic electricity pricing on network design, fleet utilization, and profitability, this research aims to provide crucial insights for airlines, aircraft manufacturers such as Elysian Aerospace, and policymakers. The findings will help clarify the economic conditions under which electric aviation can thrive, identify optimal operational strategies in a dynamic energy landscape, and contribute valuable knowledge toward the sustainable and economically viable integration of electric aircraft into the future aviation system.

References

[1] D. S. Lee et al. "The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018". In: *Atmospheric Environment* 244 (Jan. 2021), p. 117834. ISSN: 1352-2310. DOI: `10.1016/j.atmosenv.2020.117834`. URL: `https://www.sciencedirect.com/science/article/pii/S1352231020305689` (visited on 03/07/2025).

[2] Air Transport Action Group. *Tracking aviation efficiency*. Jan. 2020.

[3] Sudipta Dey Tirtha, Tanmoy Bhowmik, and Naveen Eluru. "Understanding the factors affecting airport level demand (arrivals and departures) using a novel modeling approach". In: *Journal of Air Transport Management* 106 (Jan. 2023), p. 102320. ISSN: 0969-6997. DOI: `10.1016/j.jairtraman.2022.102320`. URL: `https://www.sciencedirect.com/science/article/pii/S0969699722001399` (visited on 03/07/2025).

[4] *ACI World projects 22.3 billion passengers by 2053 | ACI World*. en-US. Feb. 2025. URL: `https://aci.aero/2025/02/26/aci-world-projects-22-3-billion-passengers-by-2053/` (visited on 03/07/2025).

[5] Connie van Uffelen. *Electric flight still a pipe dream*. en-US. Dec. 2018. URL: `https://www.tudelft.nl/en/delft-outlook/articles/electric-flight-still-a-pipe-dream` (visited on 03/07/2025).

[6] Frederico Afonso et al. "Strategies towards a more sustainable aviation: A systematic review". In: *Progress in Aerospace Sciences* 137.100878 (Feb. 2023). ISSN: 0376-0421. DOI: `10.1016/j.paerosci.2022.100878`. URL: `https://www.scopus.com/record/display.uri?eid=2-s2.0-85146416448&origin=resultslist&sort=plf-f&src=s&st1=10.1016%2fj.paerosci.2022.100878&sid=a51c9cdaf18c712771038ad38f870086&sot=b&sdt=b&sl=35&s=DOI%2810.1016%2fj.paerosci.2022.100878%29&relpos=0&citeCnt=3&searchTerm=` (visited on 03/07/2025).

[7] Candelaria Bergero et al. "Pathways to net-zero emissions from aviation". In: *Nature Sustainability* 6.4 (Apr. 2023), pp. 404–414. ISSN: 2398-9629. DOI: `10.1038/s41893-022-01046-9`. URL: `https://www.nature.com/articles/s41893-022-01046-9` (visited on 03/07/2025).

[8] Susan X. Ying. *Electric Aircraft*. en. Vol. 5. 2023. (Visited on 03/07/2025).

[9] Andreas W. Schäfer et al. "Technological, economic and environmental prospects of all-electric aircraft". In: *Nature Energy* 4.2 (Feb. 2019), pp. 160–166. ISSN: 2058-7546. DOI: `10.1038/s41560-018-0294-x`. URL: `https://www.nature.com/articles/s41560-018-0294-x` (visited on 02/11/2025).

[10] Matthieu Pettes-Duler, X. Roboam, and B. Sareni. "Integrated Optimal Design for Hybrid Electric Powertrain of Future Aircrafts". In: *Energies* (2022). DOI: `10.3390/en15186719`. URL: `https://consensus.app/papers/integrated-optimal-design-for-hybrid-electric-powertrain-pettes-duler-roboam/b566f865778f57d7b4a30586d3369a45/` (visited on 02/24/2025).

[11] Tatjana Apanasevic, Jie Li, and Marco Forzati. "eFlight: Socio-economic analysis". en. In: *ISE Research Institutes of Sweden AB* (Apr. 2021).

[12] Guan Qiao et al. "A review of electromechanical actuators for More/All Electric aircraft systems". en. In: *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science* 232.22 (Nov. 2018), pp. 4128–4151. ISSN: 0954-4062, 2041-2983. DOI: `10.1177/0954406217749869`. URL: `https://journals.sagepub.com/doi/10.1177/0954406217749869` (visited on 03/14/2025).

[13] Alan Kinene and Sebastian Birolini. "Optimization of subsidized air transport networks using electric aircraft". In: *Transportation Research Part B: Methodological* 190 (Dec. 2024), p. 103065. ISSN: 01912615. DOI: `10.1016/j.trb.2024.103065`. URL: `https://linkinghub.elsevier.com/retrieve/pii/S0191261524001899` (visited on 02/11/2025).

[14] Cedric Y. Justin et al. "Operational and Economic Feasibility of Electric Thin Haul Transportation". In: *17th AIAA Aviation Technology, Integration, and Operations Conference*. AIAA AVIATION Forum. American Institute of Aeronautics and Astronautics, June 2017. URL: `https://arc.aiaa.org/doi/10.2514/6.2017-3283` (visited on 02/28/2025).

[15] IATA. "Airfare, jet fuel price, and inflation". en. In: (Nov. 2024).

[16] Heesup Han, Jongsik Yu, and Wansoo Kim. "An electric airplane: Assessing the effect of travelers' perceived risk, attitude, and new product knowledge". In: *Journal of Air Transport Management* 78 (July 2019), pp. 33–42. ISSN: 0969-6997. DOI: `10.1016/j.jairtraman.2019.04.004`. URL: `https://www.sciencedirect.com/science/article/pii/S0969699718304915` (visited on 02/11/2025).

[17] Vamsikrishna Undavalli et al. "Recent advancements in sustainable aviation fuels". In: *Progress in Aerospace Sciences* 136 (Jan. 2023), p. 100876. ISSN: 03760421. DOI: `10.1016/j.paerosci.2022.100876`. URL: `https://linkinghub.elsevier.com/retrieve/pii/S0376042122000689` (visited on 03/13/2025).

[18] *Electric Power Systems in More and All Electric Aircraft: A Review | IEEE Journals & Magazine | IEEE Xplore*. URL: `https://ieeexplore-ieee-org.tudelft.idm.oclc.org/document/9197600` (visited on 02/12/2025).

[19] Benjamin J. Brelje and Joaquim R. R. A. Martins. "Electric, hybrid, and turboelectric fixed-wing aircraft: A review of concepts, models, and design approaches". In: *Progress in Aerospace Sciences* 104 (Jan. 2019), pp. 1–19. ISSN: 0376-0421. DOI: `10.1016/j.paerosci.2018.06.004`. URL: `https://www.sciencedirect.com/science/article/pii/S0376042118300356` (visited on 03/14/2025).

[20] Giampaolo Buticchi, Pat Wheeler, and Dushan Boroyevich. "The More-Electric Aircraft and Beyond". In: *Proceedings of the IEEE* 111.4 (Apr. 2023), pp. 356–370. ISSN: 1558-2256. DOI: `10.1109/JPROC.2022.3152995`. URL: `https://ieeexplore.ieee.org/document/9732176` (visited on 03/14/2025).

[21] Elysian Aerosapce. *Elysian Aircraft*. en. 2025. URL: `https://www.elysianaircraft.com` (visited on 03/10/2025).

[22] Reynard De Vries et al. "A New Perspective on Battery-Electric Aviation, Part II: Conceptual Design of a 90-Seater". In: *AIAA SCITECH 2024 Forum*. Orlando, FL: American Institute of Aeronautics and Astronautics, Jan. 2024. ISBN: 978-1-62410-711-5. DOI: `10.2514/6.2024-1490`. URL: `https://arc.aiaa.org/doi/10.2514/6.2024-1490` (visited on 02/11/2025).

[23] *US Dollar to Euro History: 2019*. URL: `https://www.exchangerates.org.uk/USD-EUR-spot-exchange-rates-history-2019.html` (visited on 09/23/2025).

[24] *Petroleum & Other Liquids - U.S. Energy Information Administration (EIA)*. URL: `https://www.eia.gov/petroleum/index.php` (visited on 03/14/2025).

[25] *Taking charge of electric aircraft*. URL: `https://www.aerosociety.com/news/taking-charge-of-electric-aircraft/` (visited on 02/17/2025).

[26] Stefan Baumeister, Tatjana Krstić Simić, and Emir Ganić. "Emissions reduction potentials in business aviation with electric aircraft". In: *Transportation Research Part D: Transport and Environment* 136 (Nov. 2024), p. 104415. ISSN: 1361-9209. DOI: `10.1016/j.trd.2024.104415`. URL: `https://www.sciencedirect.com/science/article/pii/S1361920924003729` (visited on 03/14/2025).

[27] van Amstel. "Optimizing the Energy and Charging Infrastructure Costs for Regional Electric Aircraft Operations". en. PhD thesis. Delft University of Technology, Mar. 2023.

[28] *The race to decarbonize electric-vehicle batteries | McKinsey*. URL: `https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/the-race-to-decarbonize-electric-vehicle-batteries` (visited on 03/14/2025).

[29] Alex Grant, David Deak, and Robert Pell. "The CO2 Impact of the 2020s' Battery Quality Lithium Hydroxide Supply Chain". en. In: (Jan. 2020).

[30] Chengjian Xu et al. "Future greenhouse gas emissions of automotive lithium-ion battery cell production". In: *Resources, Conservation and Recycling* 187 (Dec. 2022), p. 106606. ISSN: 0921-3449. DOI: `10.1016/j.resconrec.2022.106606`. URL: `https://www.sciencedirect.com/science/article/pii/S0921344922004402` (visited on 03/14/2025).

[31] Dennis L. Huff, Brenda S. Henderson, and Edmane Envia. "Motor Noise for Electric Powered Aircraft". In: *22nd AIAA/CEAS Aeroacoustics Conference*. American Institute of Aeronautics and Astronautics. URL: `https://arc.aiaa.org/doi/abs/10.2514/6.2016-2882` (visited on 03/10/2025).

[32] Christopher Kish. "An estimate of the global impact of commercial aviation noise". Thesis. Massachusetts Institute of Technology, 2008. URL: `https://dspace.mit.edu/handle/1721.1/44932` (visited on 03/14/2025).

[33] H. M. Miedema and C. G. Oudshoorn. "Annoyance from transportation noise: relationships with exposure metrics DNL and DENL and their confidence intervals". eng. In: *Environmental Health Perspectives* 109.4 (Apr. 2001), pp. 409–416. ISSN: 0091-6765. DOI: `10.1289/ehp.01109409`.

[34] *Schiphol to be quieter, cleaner and better: night closure, ban on private jets and people first.* URL: `https://news.schiphol.com/schiphol-to-be-quieter-cleaner-and-better-night-closure-ban-on-private-jets-and-people-first/` (visited on 03/14/2025).

[35] Jason Reed. *No ban on night flights and private jets – Holland Times*. en-US. Oct. 2023. URL: `https://www.hollandtimes.nl/2023-edition-7-october/no-ban-on-night-flights-and-private-jets/` (visited on 03/14/2025).

[36] *Commission adopts decision on Schiphol Airport noise reduction plan - European Commission*. en. URL: `https://transport.ec.europa.eu/news-events/news/commission-adopts-decision-schiphol-airport-noise-reduction-plan-2025-03-05_en` (visited on 03/14/2025).

[37] *ILT fines airlines for flying at night without a night slot*. URL: `https://www.schiphol.nl/en/you-and-schiphol/news/ilt-fines-airlines-for-flying-at-night-without-a-night-slot/` (visited on 03/14/2025).

[38] *Night Regime Amsterdam | ACNL*. en-US. URL: `https://slotcoordination.nl/night-regime/` (visited on 03/14/2025).

[39] FAIR. *Electric Aviation 2021 Technology Overview*. 2021.

[40] Bulent Sarlioglu and Casey T. Morris. "More Electric Aircraft: Review, Challenges, and Opportunities for Commercial Transport Aircraft". In: *IEEE Transactions on Transportation Electrification* 1.1 (June 2015), pp. 54–64. ISSN: 2332-7782. DOI: `10.1109/TTE.2015.2426499`. URL: `https://ieeexplore.ieee.org/document/7098414/?arnumber=7098414` (visited on 02/14/2025).

[41] Lorenzo Trainelli et al. "Methodologies for the initial design studies of an innovative community-friendly miniliner". en. In: *IOP Conference Series: Materials Science and Engineering* 1024.1 (Jan. 2021), p. 012109. ISSN: 1757-8981, 1757-899X. DOI: `10.1088/1757-899X/1024/1/012109`. URL: `https://iopscience.iop.org/article/10.1088/1757-899X/1024/1/012109` (visited on 03/16/2025).

[42] Smruti Sahoo, Xin Zhao, and K. Kyprianidis. "A Review of Concepts, Benefits, and Challenges for Future Electrical Propulsion-Based Aircraft". In: *Aerospace* (2020). DOI: `10.3390/aerospace7040044`. URL: `https://consensus.app/papers/a-review-of-concepts-benefits-and-challenges-for-future-sahoo-zhao/4736dc715e355a34a191778b7e9d811a/` (visited on 03/10/2025).

[43] Francesco Salucci et al. "Capturing the Demand for an Electric-Powered Short-Haul Air Transportation Network". In: *AIAA Scitech 2021 Forum*. American Institute of Aeronautics and Astronautics, Jan. 2021. URL: `https://arc.aiaa.org/doi/abs/10.2514/6.2021-0869` (visited on 02/12/2025).

[44] Hyun D. Kim, Aaron T. Perry, and Phillip J. Ansell. "A Review of Distributed Electric Propulsion Concepts for Air Vehicle Technology". In: *2018 AIAA/IEEE Electric Aircraft Technologies Symposium*. AIAA Propulsion and Energy Forum. American Institute of Aeronautics and Astronautics, July 2018. URL: `https://arc.aiaa.org/doi/10.2514/6.2018-4998` (visited on 03/10/2025).

[45] Alan H. Epstein and Steven M. O'Flarity. "Considerations for Reducing Aviation's CO2 with Aircraft Electric Propulsion". In: *Journal of Propulsion and Power* 35.3 (May 2019), pp. 572–582. ISSN: 0748-4658. DOI: `10.2514/1.B37015`. URL: `https://arc.aiaa.org/doi/10.2514/1.B37015` (visited on 03/24/2025).

[46] F. Degen et al. "Energy consumption of current and future production of lithium-ion and post lithium-ion battery cells". en. In: *Nature Energy* 8.11 (Sept. 2023), pp. 1284–1295. ISSN: 2058-7546. DOI: `10.1038/s41560-023-01355-z`. URL: `https://www.nature.com/articles/s41560-023-01355-z` (visited on 03/25/2025).

[47] Eduardo Rendondo-Iglesias, Pascal Venet, and Pelissier Serge. "Modelling Lithium-Ion Battery Ageing in Electric Vehicle Applications—Calendar and Cycling Ageing Combination Effects". en. In: *ResearchGate* (Dec. 2024). DOI: `10.3390/batteries6010014`. URL: `https://www.researchgate.net/publication/339381824_Modelling_Lithium-Ion_Battery_Ageing_in_Electric_Vehicle_Applications-Calendar_and_Cycling_Ageing_Combination_Effects` (visited on 03/25/2025).

[48] S. Micari et al. "Reliability assessment and lifetime prediction of Li-ion batteries for electric vehicles". en. In: *Electrical Engineering* 104.1 (Feb. 2022), pp. 165–177. ISSN: 1432-0487. DOI: `10.1007/s00202-021-01288-4`. URL: `https://link.springer.com/article/10.1007/s00202-021-01288-4` (visited on 03/25/2025).

[49] H Kuhn et al. "Progress and perspectives of electric air transport". In: (Sept. 2012).

[50] Committee on Propulsion and Energy Systems to Reduce Commercial Aviation Carbon Emissions et al. *Commercial Aircraft Propulsion and Energy Systems Research: Reducing Global Carbon Emissions*. Washington, D.C.: National Academies Press, 2016. ISBN: 978-0-309-44096-7. URL: `http://www.nap.edu/catalog/23490` (visited on 03/10/2025).

[51] Timothy Dever et al. "Assessment of Technologies for Noncryogenic Hybrid Electric Propulsion". In: *51st AIAA/SAE/ASEE Joint Propulsion Conference*. American Institute of Aeronautics and Astronautics, July 2015.

[52] Trym Bærheim et al. "Potential and Limitations of Battery-Powered All-Electric Regional Flights—A Norwegian Case Study". In: *IEEE Transactions on Transportation Electrification* 9.1 (Mar. 2023), pp. 1809–1825. ISSN: 2332-7782. DOI: `10.1109/TTE.2022.3200089`. URL: `https://ieeexplore.ieee.org/document/9863007` (visited on 02/18/2025).

[53] Tavish Pattanayak and Dimitri Mavris. *Battery Technology in Aviation: Current State and Future Prospects*. Dec. 2024. DOI: `10.31224/4220`. URL: `https://engrxiv.org/preprint/view/4220` (visited on 03/25/2025).

[54] Venkatasubramanian Viswanathan et al. "The challenges and opportunities of battery-powered flight". In: *Nature* 601.7894 (Jan. 2022), pp. 519–525. ISSN: 1476-4687. DOI: `10.1038/s41586-021-04139-1`. URL: `https://www.nature.com/articles/s41586-021-04139-1` (visited on 02/11/2025).

[55] Micah S. Ziegler and Jessika E. Trancik. "Re-examining rates of lithium-ion battery technology improvement and cost decline". en. In: *Energy & Environmental Science* 14.4 (Apr. 2021), pp. 1635–1651. ISSN: 1754-5706. DOI: `10.1039/D0EE02681F`. URL: `https://pubs.rsc.org/en/content/articlelanding/2021/ee/d0ee02681f` (visited on 02/18/2025).

[56] Tobias Placke et al. "Lithium-Ion, Lithium Metal and Alternative Rechargeable Battery Technologies: The Odyssey for High Energy Density". In: *ResearchGate* (July 2017). DOI: `10.1007/s10008-017-3610-7`. URL: `https://www.researchgate.net/publication/317039425_Lithium-Ion_Lithium_Metal_and_Alternative_Rechargeable_Battery_Technologies_The_Odyssey_for_High_Energy_Density` (visited on 03/25/2025).

[57] Alexander Bills et al. "Performance Metrics Required of Next-Generation Batteries to Electrify Commercial Aircraft". In: *ACS Energy Letters* 5.2 (Feb. 2020), pp. 663–668. DOI: `10.1021/acsenergylett.9b02574`. URL: `https://doi.org/10.1021/acsenergylett.9b02574` (visited on 03/25/2025).

[58] Reynard de Vries, Maurice F. M. Hoogreef, and Roelof Vos. "Range Equation for Hybrid-Electric Aircraft with Constant Power Split". In: *Journal of Aircraft* 57.3 (May 2020), pp. 552–557. ISSN: 0021-8669. DOI: `10.2514/1.C035734`. URL: `https://arc.aiaa.org/doi/10.2514/1.C035734` (visited on 03/25/2025).

[59] Rob E. Wolleswinkel et al. "A New Perspective on Battery-Electric Aviation, Part I: Reassessment of Achievable Range: AIAA SCITECH 2024 Forum". In: *Proceedings of the AIAA SCITECH 2024 Forum*. AIAA SciTech Forum and Exposition, 2024 (2024). DOI: `10.2514/6.2024-1489`. URL: `http://www.scopus.com/inward/record.url?scp=85191656297&partnerID=8YFLogxK` (visited on 02/09/2025).

[60] Finn Vehlhaber and Mauro Salazar. "Airport infrastructure sizing for a regional electric aviation network". In: 2024.

[61] Sung Wook Paek, Sangtae Kim, and Rayappan Vinoth Raj. "Optimal Endurance and Range of Electric Aircraft with Battery Degradation". en. In: *TRANSACTIONS OF THE JAPAN SOCIETY FOR AERONAUTICAL AND SPACE SCIENCES* 63.2 (2020), pp. 62–65. ISSN: 0549-3811, 2189-4205. DOI: `10.2322/tjsass.63.62`. URL: `https://www.jstage.jst.go.jp/article/tjsass/63/2/63_T-18-55/_article` (visited on 03/19/2025).

[62] Matthew Clarke and Juan Alonso. *Forecasting the Operational Lifetime of Battery-Powered Electric Aircraft Using TAPOOL Diagrams*. 2022.

[63] Ajay Misra. *Summary of 2017 NASA Workshop on Assessment of Advanced Battery Technologies for Aerospace Applications*. Jan. 2018. URL: `https://ntrs.nasa.gov/citations/20180001539` (visited on 03/10/2025).

[64] Min-Kyu Song, Yuegang Zhang, and Elton J. Cairns. "A Long-Life, High-Rate Lithium/Sulfur Cell: A Multifaceted Approach to Enhancing Cell Performance". In: *Nano Letters* 13.12 (Dec. 2013), pp. 5891–5899. ISSN: 1530-6984. DOI: `10.1021/nl402793z`. URL: `https://doi.org/10.1021/nl402793z` (visited on 03/10/2025).

[65] Yang Gao et al. "Aging mechanisms under different state-of-charge ranges and the multi-indicators system of state-of-health for lithium-ion battery with Li(NiMnCo)O2 cathode". In: *Journal of Power Sources* 400 (Oct. 2018), pp. 641–651. ISSN: 0378-7753. DOI: `10.1016/j.jpowsour.2018.07.018`. URL: `https://www.sciencedirect.com/science/article/pii/S0378775318307262` (visited on 03/25/2025).

[66] Nickolay I. Shchurov et al. "Degradation of Lithium-Ion Batteries in an Electric Transport Complex". en. In: *Energies* 14.23 (Jan. 2021), p. 8072. ISSN: 1996-1073. DOI: `10.3390/en14238072`. URL: `https://www.mdpi.com/1996-1073/14/23/8072` (visited on 03/25/2025).

[67] Sung Wook Paek, Sangtae Kim, and Christober Vinoth Raj Rayappan. "Impact of Battery Degradation on Lifetime Ranges of Electric Aircraft and Unmanned Underwater Vehicles". en. In: *2019 IEEE Conference on Control Technology and Applications (CCTA)*. Hong Kong, China: IEEE, Aug. 2019, pp. 79–85. ISBN: 978-1-7281-2767-5. DOI: `10.1109/CCTA.2019.8920412`. URL: `https://ieeexplore.ieee.org/document/8920412/` (visited on 03/19/2025).

[68] Toshiba. *High-energy type cells: SCiB™ Rechargeable battery*. URL: `https://www.global.toshiba/ww/products-solutions/battery/scib/product/cell/high-energy.html` (visited on 03/19/2025).

[69] Finn Vehlhaber and Mauro Salazar. "Electric Aircraft Assignment, Routing, and Charge Scheduling Considering the Availability of Renewable Energy". In: *IEEE Control Systems Letters* 7 (2023), pp. 3669–3674. ISSN: 2475-1456. DOI: `10.1109/LCSYS.2023.3339998`. URL: `https://ieeexplore.ieee.org/abstract/document/10345712` (visited on 02/11/2025).

[70] Alicia Holmberg. "Comparative Cost Analysis of Plug- In Charging and Battery Swapping Systems for Electric Aircraft". PhD thesis. KTH Royal Institute of Technology, Aug. 2024.

[71] Stefan Baumeister, Abraham Leung, and Tim Ryley. "The emission reduction potentials of First Generation Electric Aircraft (FGEA) in Finland". In: *Journal of Transport Geography* 85 (May 2020), p. 102730. ISSN: 0966-6923. DOI: 10.1016/j.jtrangeo.2020.102730. URL: https://www.sciencedirect.com/science/article/pii/S0966692320301551 (visited on 02/11/2025).

[72] Anne Lange, Julian Sieling, and Garoe Gonzalez Parra. "Convergence in airline operations: The case of ground times". In: *Journal of Air Transport Management* 77 (June 2019), pp. 39–45. ISSN: 0969-6997. DOI: 10.1016/j.jairtraman.2019.03.001. URL: https://www.sciencedirect.com/science/article/pii/S0969699718305052 (visited on 03/19/2025).

[73] Cedric Y. Justin, Alexia P. Payan, and Dimitri N. Mavris. "Integrated fleet assignment and scheduling for environmentally friendly electrified regional air mobility". In: *Transportation Research Part C: Emerging Technologies* 138 (May 2022), p. 103567. ISSN: 0968-090X. DOI: 10.1016/j.trc.2022.103567. URL: https://www.sciencedirect.com/science/article/pii/S0968090X22000158 (visited on 02/11/2025).

[74] Faiyaz Doctor et al. "Modelling the effect of electric aircraft on airport operations and infrastructure". In: *Technological Forecasting and Social Change* 177 (Apr. 2022), p. 121553. ISSN: 0040-1625. DOI: 10.1016/j.techfore.2022.121553. URL: https://www.sciencedirect.com/science/article/pii/S0040162522000853 (visited on 02/11/2025).

[75] Jonas Westin, Leif Olsson, and Per Åhag. "Network Design Optimization for Regional Electric Aviation in Northern Scandinavia". In: *2024 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*. Dec. 2024, pp. 400–404. DOI: 10.1109/IEEM62345.2024.10856984. URL: https://ieeexplore.ieee.org/abstract/document/10856984 (visited on 02/11/2025).

[76] P.H.L. Notten, J.H.G. Op Het Veld, and J.R.G. Van Beek. "Boostcharging Li-ion batteries: A challenging new charging concept". en. In: *Journal of Power Sources* 145.1 (July 2005), pp. 89–94. ISSN: 03787753. DOI: 10.1016/j.jpowsour.2004.12.038. URL: https://linkinghub.elsevier.com/retrieve/pii/S0378775305000728 (visited on 03/19/2025).

[77] R. Xu et al. "Disintegration of Meatball Electrodes for LiNixMnyCozO2 Cathode Materials". en. In: *Experimental Mechanics* 58.4 (Apr. 2018), pp. 549–559. ISSN: 1741-2765. DOI: 10.1007/s11340-017-0292-0. URL: https://doi.org/10.1007/s11340-017-0292-0 (visited on 03/19/2025).

[78] Madalena Pereira. "Short-range route scheduling for electric aircraft with battery-charging and battery-swapping constraints". en. PhD thesis. Delft University of Technology, Nov. 2019.

[79] Michael Schmidt et al. "Challenges for ground operations arising from aircraft concepts using alternative energy". In: *Journal of Air Transport Management*. Growing airline networks - Selected papers from the 18th ATRS World Conference, Bordeaux, France, 2014 56 (Sept. 2016), pp. 107–117. ISSN: 0969-6997. DOI: 10.1016/j.jairtraman.2016.04.023. URL: https://www.sciencedirect.com/science/article/pii/S096969971630165X (visited on 02/11/2025).

[80] Gaston Tissandier. *La Navigation Aérienne: L'aviation et la direction des aérostats dans les temps anciens et modernes*. Paris: Hachette et Cie, 1886.

[81] Francessco Barato. *Preliminary assessment of turbomachinery configurations for an intercooled-recuperated microturbine electric generato*. Università degli Studi di Padova.

[82] Martin Hepperle. "Electric Flight – Potential and Limitations". en. In: (Oct. 2012).

[83] Angela Satterlee. *Reintroducing Solar Riser: The World's First Crewed Solar-Powered Aircraft - Hangar Flying*. Aug. 2024. URL: https://inspire.eaa.org/2024/08/22/reintroducing-solar-riser-the-worlds-first-crewed-solar-powered-aircraft/ (visited on 03/10/2025).

[84] Martyn Cowley. "solar challenger". en. In: (June 1981).

[85] NASA. *Solar-Power Research and Dryden*. Oct. 1998.

[86] *Helios Prototype: The forerunner of 21st century solar-powered "atmospheric satellites"*.

[87] *Taurus Electro*. en-US. URL: https://www.pipistrel-aircraft.com/products/taurus-electro/ (visited on 03/10/2025).

[88] Damian Carrington. "Solar plane makes history after completing round-the-world trip". en-GB. In: *The Guardian* (July 2016). ISSN: 0261-3077. URL: `https://www.theguardian.com/env ironment/2016/jul/26/solar-impulse-plane-makes-history-completing-round-the-world-trip` (visited on 03/10/2025).

[89] Kate Sarsfield June 2020. *Pipistrel Velis Electro earns first all-electric aircraft type certification*. URL: `https://www.flightglobal.com/news/pipistrel-velis-electro-earns-first-all-electric-aircraft-type-certification/138779.article` (visited on 03/10/2025).

[90] L. Gogolák et al. "Possibilities of optimizing fuel consumption in hybrid and electronic airplanes". In: *Analecta Technica Szegedinensia* (2019). DOI: `10.14232/analecta.2019.2.65-76`. URL: `https://consensus.app/papers/possibilities-of-optimizing-fuel-consumption-in-hybrid-gogol%C3%A1k-csik%C3%B3s/248754bc7ff15fc0afa7c1f19502ec69/` (visited on 03/10/2025).

[91] *The Wright Spirit*. URL: `https://www.weflywright.com/aircraft` (visited on 03/10/2025).

[92] Ben Sampson. *Wright Electric validates motor safety at high altitude*. en-GB. Feb. 2024. URL: `https://www.aerospacetestinginternational.com/news/electric-hybrid/wright-elect ric-validates-motor-safety-at-high-altitude.html` (visited on 03/10/2025).

[93] *Maeve Unveils Plans For 80-Seat Hybrid Regional Airliner | Aviation Week Network*. URL: `https://aviationweek-com.tudelft.idm.oclc.org/aerospace/aircraft-propulsion/maeve-unveils-plans-80-seat-hybrid-regional-airliner` (visited on 03/10/2025).

[94] *ES-30™ | Heart Aerospace*. en-US. URL: `https://heartaerospace.com/es-30/` (visited on 03/10/2025).

[95] *RX4E 4 seat electric aircraft*. en. URL: `https://flyone.com.au/rx4e` (visited on 03/10/2025).

[96] *Aircraft – Eviation*. en-US. 2025. URL: `https://www.eviation.com/aircraft/` (visited on 03/10/2025).

[97] *Velis Electro*. en-US. URL: `https://www.pipistrel-aircraft.com/products/velis-electr o/` (visited on 03/10/2025).

[98] *Beta ALIA*. en. URL: `https://beta.team/aircraft` (visited on 03/10/2025).

[99] *Lilium | EIT*. URL: `https://eit.europa.eu/news-events/success-stories/lilium` (visited on 03/10/2025).

[100] Lilium. *Lilium*. en. URL: `https://jet.lilium.com/` (visited on 03/10/2025).

[101] Joby Aviation. *Q4 2024 Shareholder Letter*. Feb. 2025.

[102] *Joby Aviation S4 2.0 (pre-production prototype)*. URL: `https://evtol.news/joby-s4` (visited on 03/10/2025).

[103] Flightradar24. *Live Flight Tracker - Real-Time Flight Tracker Map*. en. URL: `https://www.flightradar24.com/` (visited on 03/19/2025).

[104] *Annex 6 to the Convention on International Civil Aviation*. Nov. 2018.

[105] AFS-200. *ICAO FPFM Overview, flight planning, Fuel Monitoring, Performance Based Contingency Fuel*. Oct. 2021.

[106] *Extended diversion time operations (EDTO) manual*. First edition. Montréal: International Civil Aviation Organization, 2017. ISBN: 978-92-9258-327-9.

[107] Frédéric Dobruszkes and Didier Peeters. "The magnitude of detours faced by commercial flights: A global assessment". In: *Journal of Transport Geography* 79 (July 2019), p. 102465. ISSN: 0966-6923. DOI: `10.1016/j.jtrangeo.2019.102465`. URL: `https://www.sciencedirect.com/science/article/pii/S0966692318305544` (visited on 06/06/2025).

[108] Jan Vespermann and Andreas Wald. "Much Ado about Nothing? – An analysis of economic impacts and ecologic effects of the EU-emission trading scheme in the aviation industry". In: *Transportation Research Part A: Policy and Practice*. A Collection of Papers:Transportation in a World of Climate Change 45.10 (Dec. 2011), pp. 1066–1076. ISSN: 0965-8564. DOI: `10.1016/ j.tra.2010.03.005`. URL: `https://www.sciencedirect.com/science/article/pii/ S0965856410000443` (visited on 03/19/2025).

[109] *Aviation fuel*. Dec. 2024. URL: `https://en.wikipedia.org/w/index.php?title=Aviation_fuel&oldid=1262419437` (visited on 03/23/2025).

[110] *Fact Sheet: Sustainable Aviation Fuel: Technical Certification*.

[111] *What are Sustainable Aviation Fuels? | EASA*. URL: `https://www.easa.europa.eu/en/domains/environment/eaer/sustainable-aviation-fuels/what-are-sustainable-aviation-fuels` (visited on 11/28/2025).

[112] *Alternative Fuels Data Center: Sustainable Aviation Fuel*. URL: `https://afdc.energy.gov/fuels/sustainable-aviation-fuel` (visited on 03/23/2025).

[113] Matthias Braun, Wolfgang Grimme, and Katrin Oesingmann. "Pathway to net zero: Reviewing sustainable aviation fuels, environmental impacts and pricing". In: *Journal of Air Transport Management* 117 (May 2024), p. 102580. ISSN: 0969-6997. DOI: `10.1016/j.jairtraman.2024.102580`. URL: `https://www.sciencedirect.com/science/article/pii/S0969699724000450` (visited on 03/23/2025).

[114] IATA. *Fact Sheet Fuel*. 2024.

[115] *Avgas*. Feb. 2025. URL: `https://en.wikipedia.org/w/index.php?title=Avgas&oldid=1275936738` (visited on 03/23/2025).

[116] Capt Lim. *What happened to passenger planes with propeller engines? Are they all gone now? – From the Skies to the Bar*. en-US. URL: `https://askcaptainlim.com/what-happened-to-passenger-planes-with-propeller-engines-are-they-all-gone-now/` (visited on 03/23/2025).

[117] *Jet Fuel Price Trend, Index 2025, Chart and Forecast*. en. URL: `https://www.imarcgroup.com/jet-fuel-price-trend` (visited on 11/19/2025).

[118] Jaap Brouwer et al. *How airlines could adapt to rising fuel prices*. McKinsey.com. July 2022. URL: `https://www.mckinsey.com/industries/travel/our-insights/why-rising-fuel-prices-might-not-be-as-bad-for-the-airline-sector-as-it-seems` (visited on 03/25/2025).

[119] opisteam. *Jet Fuel Pricing 101*. source. July 2023. URL: `https://www.opisnet.com/blog/jetfuel/` (visited on 03/25/2025).

[120] Serhan Cevik. "Shocked: Electricity Price Volatility Spillovers in Europe". en. In: *IMF Working Papers* 2025.007 (Jan. 2025), p. 1. ISSN: 1018-5941. DOI: `10.5089/9798400296901.001`. URL: `https://elibrary.imf.org/openurl?genre=journal&issn=1018-5941&volume=2025&issue=007&cid=559701-com-dsp-crossref` (visited on 03/07/2025).

[121] FuelsEurope. *Statistics*. en. Nov. 2024. URL: `https://www.fuelseurope.eu/statistics` (visited on 03/25/2025).

[122] *Jet Fuel: From Well to Wing*. Jan. 2018. URL: `https://www.airlines.org/wp-content/uploads/2018/01/jet-fuel-1.pdf` (visited on 03/25/2025).

[123] Bill Hemmings. *Taxing aviation fuel in the EU*. June 2019.

[124] *Weekly Oil Bulletin*. en. URL: `https://energy.ec.europa.eu/data-and-analysis/weekly-oil-bulletin_en` (visited on 03/25/2025).

[125] Marc Naumann and Leena Suhl. "How does fuel price uncertainty affect strategic airline planning?" en. In: *Operational Research* 13.3 (Oct. 2013), pp. 343–362. ISSN: 1866-1505. DOI: `10.1007/s12351-012-0131-0`. URL: `https://link.springer.com/article/10.1007/s12351-012-0131-0` (visited on 02/24/2025).

[126] Peter Morrell and William Swan. "Airline Jet Fuel Hedging: Theory and Practice". en. In: *Transport Reviews* 26.6 (Nov. 2006), pp. 713–730. ISSN: 0144-1647, 1464-5327. DOI: `10.1080/01441640600679524`. URL: `http://www.tandfonline.com/doi/abs/10.1080/01441640600679524` (visited on 03/23/2025).

[127] *European airlines gain €5bn from hedging as oil prices soar after invasion of Ukraine*. en-US. Mar. 2022. URL: `https://www.eurofinance.com/news/european-airlines-gain-e5bn-from-hedging-as-oil-prices-soar-after-invasion-of-ukraine/` (visited on 03/23/2025).

[128] *European airlines may quit fuel hedging after $4.66 billion in losses*. en-US. Dec. 2020. URL: `https://www.eurofinance.com/news/european-airlines-may-quit-fuel-hedging-after-4-66-billion-in-losses/` (visited on 03/23/2025).

[129] Siew Hoon Lim and Yongtao Hong. "Fuel hedging and airline operating costs". en. In: *Journal of Air Transport Management* 36 (Apr. 2014), pp. 33–40. ISSN: 09696997. DOI: `10.1016/j.jairtraman.2013.12.009`. URL: `https://linkinghub.elsevier.com/retrieve/pii/S0969699713001531` (visited on 03/23/2025).

[130] Juhani Rantaniemi et al. "A Study on the Impact of Distance-Based Value Loss on Transmission Network Power Flow Using Synthetic Networks". en. In: *Energies* 15.2 (Jan. 2022), p. 423. ISSN: 1996-1073. DOI: `10.3390/en15020423`. URL: `https://www.mdpi.com/1996-1073/15/2/423` (visited on 03/12/2025).

[131] Evasio Lavagno. "Risk of Energy Availability: Common Corridors for Europe Supply Security". en. In: (Dec. 2010).

[132] International Energy Agency Energy Technology Systems Analysis Programme. *Electricity Transmission and Distribution*. Apr. 2014.

[133] *(PDF) Battery Technology in Aviation: Current State and Future Prospects*. Dec. 2024. URL: `https://www.researchgate.net/publication/387043496_Battery_Technology_in_Aviation_Current_State_and_Future_Prospects` (visited on 03/25/2025).

[134] *Transmission and distribution losses by country*. en. URL: `https://www.statista.com/statistics/246481/transmission-and-distribution-losses-in-selected-countries/` (visited on 03/11/2025).

[135] *European Electricity Review 2024*. en-US. 2024. URL: `https://ember-energy.org/latest-insights/european-electricity-review-2024` (visited on 03/13/2025).

[136] "How much can electric aircraft contribute to reaching the Flightpath 2050 CO2 emissions goal? A system dynamics approach for european short haul flights | Request PDF". en. In: *ResearchGate* (Dec. 2024). DOI: `10.1016/j.jairtraman.2023.102455`. URL: `https://www.researchgate.net/publication/372494545_How_much_can_electric_aircraft_contribute_to_reaching_the_Flightpath_2050_CO2_emissions_goal_A_system_dynamics_approach_for_european_short_haul_flights` (visited on 02/17/2025).

[137] *Live 24/7 CO□ emissions of electricity consumption*. Electricity Maps. June 2025. URL: `https://app.electricitymaps.com/map/72h/hourly` (visited on 03/07/2025).

[138] Counsil of European Union. *How is EU electricity produced and sold?* en. Jan. 2025. URL: `https://www.consilium.europa.eu/en/infographics/how-is-eu-electricity-produced-and-sold/` (visited on 03/13/2025).

[139] Karin Van Der Wiel et al. "The influence of weather regimes on European renewable energy production and demand". In: *Environmental Research Letters* 14.9 (Sept. 2019), p. 094010. ISSN: 1748-9326. DOI: `10.1088/1748-9326/ab38d3`. URL: `https://iopscience.iop.org/article/10.1088/1748-9326/ab38d3` (visited on 03/13/2025).

[140] Ana C. R. Gonçalves et al. "Extreme weather events on energy systems: a comprehensive review on impacts, mitigation, and adaptation measures". In: *Sustainable Energy Research* 11.1 (Jan. 2024), p. 4. ISSN: 2731-9237. DOI: `10.1186/s40807-023-00097-6`. URL: `https://doi.org/10.1186/s40807-023-00097-6` (visited on 03/13/2025).

[141] Stephania Mosquera-López, Jorge M. Uribe, and Orlando Joaqui-Barandica. "Weather conditions, climate change, and the price of electricity". en. In: *Energy Economics* 137 (Sept. 2024), p. 107789. ISSN: 01409883. DOI: `10.1016/j.eneco.2024.107789`. URL: `https://linkinghub.elsevier.com/retrieve/pii/S0140988324004973` (visited on 03/17/2025).

[142] Finn Vehlhaber and Mauro Salazar. *A Model Predictive Control Scheme for Flight Scheduling and Energy Management of Electric Aviation Networks*. Apr. 2024. DOI: `10.48550/arXiv.2404.09282`. URL: `http://arxiv.org/abs/2404.09282` (visited on 02/24/2025).

[143]   Alexander Souza Block et al. "Investigating dynamic conditional correlation between crude oil and fuels in non-linear framework: The financial and economic role of structural breaks". In: *Energy Economics* 49 (May 2015), pp. 23–32. ISSN: 0140-9883. DOI: `10.1016/j.eneco.2015.01.011`. URL: `https://www.sciencedirect.com/science/article/pii/S0140988315000250` (visited on 03/13/2025).

[144]   Aviral Kumar Tiwari et al. "Analyzing the connectedness between crude oil and petroleum products: Evidence from USA". en. In: *International Journal of Finance & Economics* 28.3 (2023), pp. 2278–2347. ISSN: 1099-1158. DOI: `10.1002/ijfe.2536`. URL: `https://onlinelibrary.wiley.com/doi/abs/10.1002/ijfe.2536` (visited on 03/13/2025).

[145]   *Crack Spread: What it is, How to Trade It*. en. URL: `https://www.investopedia.com/terms/c/crackspread.asp` (visited on 03/13/2025).

[146]   Tom Arnold. *Why Low Oil Prices Mean Higher Electricity Prices | T&D Costs*. en-US. Jan. 2015. URL: `https://gridium.com/why-low-oil-prices-mean-higher-electricity-prices/` (visited on 03/13/2025).

[147]   European Central Bank. "Oil prices and euro area consumer energy prices". en. In: *ECB Economic Bulletin* Issue 2 (2016).

[148]   Christian Lutz et al. *Electricity Costs of Energy Intensive Industries An International Comparison*. en. 2015. DOI: `10.13140/RG.2.1.2442.9286`. URL: `http://rgdoi.net/10.13140/RG.2.1.2442.9286` (visited on 03/13/2025).

[149]   *Soaring fossil gas costs responsible for EU electricity price increase*. en-US. URL: `https://ember-energy.org/latest-insights/soaring-fossil-gas-costs-responsible-for-eu-electricity-price-increase` (visited on 03/13/2025).

[150]   L. D. Menezes, M. Houllier, and M. Tamvakis. "Time-varying convergence in European electricity spot markets and their association with carbon and fuel prices". In: *Energy Policy* 88 (2016), pp. 613–627. DOI: `10.1016/J.ENPOL.2015.09.008`. URL: `https://consensus.app/papers/timevarying-convergence-in-european-electricity-spot-menezes-houllier/80941c86c0c35d4989d174542ba5805f/` (visited on 03/11/2025).

[151]   E. J. van Enter. "Energy consumption of baggage handling systems". en. In: (2018). URL: `https://repository.tudelft.nl/record/uuid:1501d592-3a86-4e8c-bb8d-c3c1772d2378` (visited on 03/11/2025).

[152]   Boya Hou et al. "Impact of Aviation Electrification on Airports: Flight Scheduling and Charging". In: *IEEE Transactions on Intelligent Transportation Systems* 25.3 (Mar. 2024), pp. 2342–2354. ISSN: 1524-9050, 1558-0016. DOI: `10.1109/TITS.2023.3324310`. URL: `https://ieeexplore.ieee.org/document/10296862/` (visited on 02/17/2025).

[153]   Gwendolyn Brown. *Making Sense of Demand Charges: What Are They and How Do They Work?* en-US. June 2017. URL: `https://www.renewableenergyworld.com/solar/utility-scale/making-sense-of-demand-charges-what-are-they-and-how-do-they-work/` (visited on 03/26/2025).

[154]   Tom van Santen. *Interview with ROCC employee*. Dutch. Mar. 2025.

[155]   *Electricity price statistics*. en. URL: `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Electricity_price_statistics` (visited on 03/07/2025).

[156]   European Commission. *Excise Duties: Other Energy Tax Legislation - European Commission*. en. 2025. URL: `https://taxation-customs.ec.europa.eu/excise-duties-other-energy-tax-legislation_en` (visited on 03/13/2025).

[157]   Katrin Oesingmann. "The impact of economic agreements and environmental instruments on air transport demand:" in: *MSc. Thesis* (Apr. 2022).

[158]   Friedrich Thießen. "Taxes and Fees". en. In: *Air Transport and its Subsidies*. Ed. by Friedrich Thießen. Wiesbaden: Springer Fachmedien, 2022, pp. 7–21. ISBN: 978-3-658-38899-7. URL: `https://doi.org/10.1007/978-3-658-38899-7_2` (visited on 03/13/2025).

[159]   Eckhard Pache. *Implementation of Kerosene Fuel Taxation in Europe Part I: Legal Foundations and Issues*. June 2019.

[160] A4E. *A4e's position on the energy taxation directive*. Apr. 2023.

[161] Tobias Grosche. "Airline Scheduling Process". en. In: *Computational Intelligence in Integrated Airline Scheduling*. Springer, Berlin, Heidelberg, 2009, pp. 7–46. ISBN: 978-3-540-89887-0. URL: `https://link.springer.com/chapter/10.1007/978-3-540-89887-0_2` (visited on 03/11/2025).

[162] Lei Zhou et al. "Airline planning and scheduling: Models and solution methodologies". en. In: *Frontiers of Engineering Management* 7.1 (Mar. 2020), pp. 1–26. ISSN: 2096-0255. DOI: `10.1007/s42524-020-0093-5`. URL: `https://doi.org/10.1007/s42524-020-0093-5` (visited on 03/11/2025).

[163] Bruno F Santos. *Lecture 2 (Part II) – Demand Forecast*. en. AE4423. Delft University of Technology.

[164] Maximilian M. Etschmaier and Dennis F. X. Mathaisel. "Airline Scheduling: An Overview". en. In: *Transportation Science* 19.2 (May 1985), pp. 127–138. ISSN: 0041-1655, 1526-5447. DOI: `10.1287/trsc.19.2.127`. URL: `https://pubsonline.informs.org/doi/10.1287/trsc.19.2.127` (visited on 03/21/2025).

[165] Vahid Zeighami and François Soumis. "Combining Benders' Decomposition and Column Generation for Integrated Crew Pairing and Personalized Crew Assignment Problems". In: *Transportation Science* 53.5 (Sept. 2019), pp. 1479–1499. ISSN: 0041-1655. DOI: `10.1287/trsc.2019.0892`. URL: `https://pubsonline.informs.org/doi/10.1287/trsc.2019.0892` (visited on 03/11/2025).

[166] Shengzhi Shao, Hanif D. Sherali, and Mohamed Haouari. "A Novel Model and Decomposition Approach for the Integrated Airline Fleet Assignment, Aircraft Routing, and Crew Pairing Problem". In: *Transportation Science* 51.1 (Feb. 2017), pp. 233–249. ISSN: 0041-1655. DOI: `10.1287/trsc.2015.0623`. URL: `https://pubsonline.informs.org/doi/10.1287/trsc.2015.0623` (visited on 03/11/2025).

[167] Abdelrahman EE Eltoukhy, Felix TS Chan, and S. H. Chung. "Airline schedule planning: a review and future directions". English. In: *Industrial Management & Data Systems* 117.6 (2017), pp. 1201–1243. ISSN: 02635577. DOI: `10.1108/IMDS-09-2016-0358`. URL: `https://www.proquest.com/docview/1915806409/abstract/F164B36FAD774027PQ/1` (visited on 03/03/2025).

[168] Amedeo R. Odoni, Cynthia Barnhart, and Peter P. Belobaba, eds. *The global airline industry*. en. Aerospace series. Chichester, U.K: Wiley, 2009. ISBN: 978-0-470-74077-4 978-0-470-74472-7 978-0-470-74473-4 978-1-60086-702-6.

[169] Bruno F Santos. "Lecture I (Part II) – Multi-commodity Flow Models". en. In: (2024).

[170] IATA. *Chart of the Week: Balancing fleet age for efficiency and sustainable growth*. Sept. 2023.

[171] Justin Hayward. *The Rise And Fall Of The Airbus A380*. en. Nov. 2020. URL: `https://simpleflying.com/a380-rise-and-fall/` (visited on 03/21/2025).

[172] IATA. *Chart of the Week: More aircraft are leased than owned by airlines globally*. Apr. 2024.

[173] Cynthia Barnhart, Timothy S. Kniker, and Manoj Lohatepanont. "Itinerary-Based Airline Fleet Assignment". en. In: *Transportation Science* 36.2 (May 2002), pp. 199–217. ISSN: 0041-1655, 1526-5447. DOI: `10.1287/trsc.36.2.199.566`. URL: `https://pubsonline.informs.org/doi/10.1287/trsc.36.2.199.566` (visited on 02/26/2025).

[174] Dušan Teodorović, Milica Kalić, and Goran Pavković. "The potential for using fuzzy set theory in airline network design". In: *Transportation Research Part B: Methodological* 28.2 (Apr. 1994), pp. 103–121. ISSN: 0191-2615. DOI: `10.1016/0191-2615(94)90020-5`. URL: `https://www.sciencedirect.com/science/article/pii/0191261594900205` (visited on 02/17/2025).

[175] Patrick Jaillet, Gao Song, and Gang Yu. "Airline network design and hub location problems". In: *Location Science*. Hub Location 4.3 (Oct. 1996), pp. 195–212. ISSN: 0966-8349. DOI: `10.1016/S0966-8349(96)00016-2`. URL: `https://www.sciencedirect.com/science/article/pii/S0966834996000162` (visited on 03/03/2025).

[176] Nicole Adler and Karen Smilowitz. "Hub-and-spoke network alliances and mergers: Price-location competition in the airline industry". In: *Transportation Research Part B: Methodological* 41.4 (May 2007), pp. 394–409. ISSN: 0191-2615. DOI: 10.1016/j.trb.2006.06.005. URL: https://www.sciencedirect.com/science/article/pii/S0191261506000907 (visited on 03/21/2025).

[177] Sibel A. Alumur, Bahar Y. Kara, and Oya E. Karasan. "The design of single allocation incomplete hub networks". en. In: *Transportation Research Part B: Methodological* 43.10 (2009), pp. 936–951. URL: https://ideas.repec.org//a/eee/transb/v43y2009i10p936-951.html (visited on 03/21/2025).

[178] Qiang Meng and Xinchang Wang. "Intermodal hub-and-spoke network design: Incorporating multiple stakeholders and multi-type containers". In: *Transportation Research Part B: Methodological* 45.4 (May 2011), pp. 724–742. ISSN: 0191-2615. DOI: 10.1016/j.trb.2010.11.002. URL: https://www.sciencedirect.com/science/article/pii/S0191261510001359 (visited on 03/21/2025).

[179] Manoj Lohatepanont and Cynthia Barnhart. "Airline Schedule Planning: Integrated Models and Algorithms for Schedule Design and Fleet Assignment". English. In: *Transportation Science* 38.1 (Feb. 2004), pp. 19–32. ISSN: 00411655. URL: https://www.proquest.com/docview/203556471/citation/16B0E85F10A14138PQ/1 (visited on 03/11/2025).

[180] A. Ghobrial and A. Kanafani. "Quality-of-Service Model of Intercity Air-Travel Demand". en. In: *Journal of Transportation Engineering* 121.2 (Mar. 1995), pp. 135–140. ISSN: 0733-947X, 1943-5436. DOI: 10.1061/(ASCE)0733-947X(1995)121:2(135). URL: https://ascelibrary.org/doi/10.1061/%28ASCE%290733-947X%281995%29121%3A2%28135%29 (visited on 03/11/2025).

[181] Philippe Barla and Christos Constantatos. "Airline network structure under demand uncertainty". en. In: *Transportation Research Part E: Logistics and Transportation Review* 36.3 (Sept. 2000), pp. 173–180. ISSN: 13665545. DOI: 10.1016/S1366-5545(99)00031-9. URL: https://linkinghub.elsevier.com/retrieve/pii/S1366554599000319 (visited on 03/26/2025).

[182] Rajesh Mirani and Albert L. Lederer. "An Instrument for Assessing the Organizational Benefits of IS Projects". en. In: *Decision Sciences* 29.4 (1998), pp. 803–838. ISSN: 1540-5915. DOI: 10.1111/j.1540-5915.1998.tb00878.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-5915.1998.tb00878.x (visited on 03/11/2025).

[183] Oliver W. Wojahn. "The Impact of Passengers' Preferences regarding Time and Service Quality on Airline Network Structure". In: *Journal of Transport Economics and Policy* 36.1 (2002), pp. 139–162. ISSN: 0022-5258. URL: https://www.jstor.org/stable/20053896 (visited on 03/03/2025).

[184] Chaug-Ing Hsu and Yuh-Horng Wen. "Determining flight frequencies on an airline network with demand–supply interactions". In: *Transportation Research Part E: Logistics and Transportation Review* 39.6 (Nov. 2003), pp. 417–441. ISSN: 1366-5545. DOI: 10.1016/S1366-5545(02)00060-1. URL: https://www.sciencedirect.com/science/article/pii/S1366554502000601 (visited on 03/26/2025).

[185] Thiago Dias de Jesus, Marcelo Seido Nagano, and Victor Rafael Rezende Celestino. "An integrated frequency assignment and fleet assignment model: A strategic application in the Brazilian regional aviation market". In: *Transport Economics and Management* 1 (Dec. 2023), pp. 151–159. ISSN: 2949-8996. DOI: 10.1016/j.team.2023.09.001. URL: https://www.sciencedirect.com/science/article/pii/S2949899623000138 (visited on 03/03/2025).

[186] Phillip J. Lederer and Ramakrishnan S. Nambimadom. "Airline Network Design". In: *Operations Research* 46.6 (Dec. 1998), pp. 785–804. ISSN: 0030-364X. DOI: 10.1287/opre.46.6.785. URL: https://pubsonline.informs.org/doi/10.1287/opre.46.6.785 (visited on 03/21/2025).

[187] Wenbin Wei and Mark Hansen. "An aggregate demand model for air passenger traffic in the hub-and-spoke network". In: *Transportation Research Part A: Policy and Practice* 40.10 (Dec. 2006), pp. 841–851. ISSN: 0965-8564. DOI: 10.1016/j.tra.2005.12.012. URL: https://www.sciencedirect.com/science/article/pii/S0965856406000218 (visited on 02/11/2025).

[188] Hanif D. Sherali and Xiaomei Zhu. "Two-Stage Fleet Assignment Model Considering Stochastic Passenger Demands". In: *Operations Research* 56.2 (Apr. 2008), pp. 383–399. ISSN: 0030-364X. DOI: 10.1287/opre.1070.0476. URL: https://pubsonline.informs.org/doi/10.1287/opre.1070.0476 (visited on 02/26/2025).

[189] Ming Liu et al. "Green Airline-Fleet Assignment with Uncertain Passenger Demand and Fuel Price". en. In: *Sustainability* 15.2 (Jan. 2023), p. 899. ISSN: 2071-1050. DOI: 10.3390/su15020899. URL: https://www.mdpi.com/2071-1050/15/2/899 (visited on 02/11/2025).

[190] Hooi Ling Khoo and Lay Eng Teoh. "A bi-objective dynamic programming approach for airline green fleet planning". In: *Transportation Research Part D: Transport and Environment* 33 (Dec. 2014), pp. 166–185. ISSN: 1361-9209. DOI: 10.1016/j.trd.2014.06.003. URL: https://www.sciencedirect.com/science/article/pii/S1361920914000686 (visited on 02/28/2025).

[191] H. Sherali, E. Bish, and Xiaomei Zhu. "Airline fleet assignment concepts, models, and algorithms". In: *Eur. J. Oper. Res.* 172 (2006), pp. 1–30. DOI: 10.1016/j.ejor.2005.01.056. URL: https://consensus.app/papers/airline-fleet-assignment-concepts-models-and-algorithms-sherali-bish/4cb256f2a1fa5c5f946cf2505a6ddaf6/ (visited on 02/24/2025).

[192] Christopher A. Hane et al. "The fleet assignment problem: Solving a large-scale integer program". en. In: *Mathematical Programming* 70.1 (Oct. 1995), pp. 211–232. ISSN: 1436-4646. DOI: 10.1007/BF01585938. URL: https://doi.org/10.1007/BF01585938 (visited on 03/21/2025).

[193] Slavica Dožić et al. "Variable Neighborhood Search to solve an airline fleet sizing and fleet assignment problem". In: *Transportation Research Procedia*. 21st EURO Working Group on Transportation Meeting, EWGT 2018, 17th – 19th September 2018, Braunschweig, Germany 37 (Jan. 2019), pp. 258–265. ISSN: 2352-1465. DOI: 10.1016/j.trpro.2018.12.191. URL: https://www.sciencedirect.com/science/article/pii/S2352146518306069 (visited on 03/21/2025).

[194] Nabil Kenan, Aida Jebali, and Ali Diabat. "An integrated flight scheduling and fleet assignment problem under uncertainty". In: *Computers & Operations Research* 100 (Dec. 2018), pp. 333–342. ISSN: 0305-0548. DOI: 10.1016/j.cor.2017.08.014. URL: https://www.sciencedirect.com/science/article/pii/S0305054817302216 (visited on 03/21/2025).

[195] Amin Jamili. "A robust mathematical model and heuristic algorithms for integrated aircraft routing and scheduling, with consideration of fleet assignment problem". In: *Journal of Air Transport Management* 58 (Jan. 2017), pp. 21–30. ISSN: 0969-6997. DOI: 10.1016/j.jairtraman.2016.08.008. URL: https://www.sciencedirect.com/science/article/pii/S0969699716301168 (visited on 03/21/2025).

[196] Rigas Doganis. *Flying off Course: Airline Economics and Marketing*. London, UNITED KINGDOM: Routledge, 2010. ISBN: 978-0-203-86399-2. URL: http://ebookcentral.proquest.com/lib/delft/detail.action?docID=472501 (visited on 03/11/2025).

[197] Mikael Faa. "Potential network planning for electric aircraft". PhD thesis. Haaga Helia, 2022.

[198] Keji Wei, Vikrant Vaze, and Alexandre Jacquillat. "Airline Timetable Development and Fleet Assignment Incorporating Passenger Choice". In: *Transportation Science* 54.1 (Jan. 2020), pp. 139–163. ISSN: 0041-1655. DOI: 10.1287/trsc.2019.0924. URL: https://pubsonline.informs.org/doi/10.1287/trsc.2019.0924 (visited on 03/11/2025).

[199] Tobias Grosche, Franz Rothlauf, and Armin Heinzl. "Gravity models for airline passenger volume estimation". In: *Journal of Air Transport Management* 13.4 (July 2007), pp. 175–183. ISSN: 0969-6997. DOI: 10.1016/j.jairtraman.2007.02.001. URL: https://www.sciencedirect.com/science/article/pii/S0969699707000178 (visited on 03/11/2025).

[200] Thijs Boonekamp, Joost Zuidberg, and Guillaume Burghouwt. "Determinants of air travel demand: The role of low-cost carriers, ethnic links and aviation-dependent employment". In: *Transportation Research Part A: Policy and Practice*. 2016 ATRS Conference 112 (June 2018), pp. 18–28. ISSN: 0965-8564. DOI: 10.1016/j.tra.2018.01.004. URL: https://www.sciencedirect.com/science/article/pii/S0965856418300156 (visited on 03/11/2025).

[201] Sebastian Birolini et al. "Airline Network Planning: Mixed-integer non-convex optimization with demand–supply interactions". In: *Transportation Research Part B: Methodological* 154 (Dec. 2021), pp. 100–124. ISSN: 0191-2615. DOI: 10.1016/j.trb.2021.09.003. URL: https://www.sciencedirect.com/science/article/pii/S0191261521001703 (visited on 03/11/2025).

[202] Cedric Y. Justin, Alexia P. Payan, and Dimitri Mavris. "Demand Modeling and Operations Optimization for Advanced Regional Air Mobility". In: *AIAA AVIATION 2021 FORUM*. AIAA AVIATION Forum. American Institute of Aeronautics and Astronautics, July 2021. URL: https://arc.aiaa.org/doi/10.2514/6.2021-3179 (visited on 02/28/2025).

[203] Sebastian Birolini et al. *Con-Accessibility: Logit-Based Catchment Area Modeling for Strategic Airport System Planning*. en. SSRN Scholarly Paper. Rochester, NY, Mar. 2024. DOI: 10.2139/ssrn.4760790. URL: https://papers.ssrn.com/abstract=4760790 (visited on 03/26/2025).

[204] Ho-Yin Mak, Ying Rong, and Zuo-Jun Max Shen. "Infrastructure Planning for Electric Vehicles with Battery Swapping". In: *Management Science* 59.7 (July 2013), pp. 1557–1575. ISSN: 0025-1909. DOI: 10.1287/mnsc.1120.1672. URL: https://pubsonline.informs.org/doi/10.1287/mnsc.1120.1672 (visited on 02/18/2025).

[205] Mushfiqur R. Sarker, Hrvoje Pandžić, and Miguel A. Ortega-Vazquez. "Optimal Operation and Services Scheduling for an Electric Vehicle Battery Swapping Station". In: *IEEE Transactions on Power Systems* 30.2 (Mar. 2015), pp. 901–910. ISSN: 1558-0679. DOI: 10.1109/TPWRS.2014.2331560. URL: https://ieeexplore.ieee.org/document/6857439 (visited on 02/13/2025).

[206] Wenxia Liu et al. "A New Method to Plan the Capacity and Location of Battery Swapping Station for Electric Vehicle Considering Demand Side Management". en. In: *Sustainability* 8.6 (June 2016), p. 557. ISSN: 2071-1050. DOI: 10.3390/su8060557. URL: https://www.mdpi.com/2071-1050/8/6/557 (visited on 02/18/2025).

[207] Owen Worley and Diego Klabjan. "Optimization of battery charging and purchasing at electric vehicle battery swap stations". In: *2011 IEEE Vehicle Power and Propulsion Conference*. Sept. 2011, pp. 1–4. DOI: 10.1109/VPPC.2011.6043182. URL: https://ieeexplore.ieee.org/document/6043182/?arnumber=6043182 (visited on 02/18/2025).

[208] Andy Ham and Myoung-Ju Park. "Electric Vehicle Route Optimization Under Time-of-Use Electricity Pricing". In: *IEEE Access* 9 (2021), pp. 37220–37228. ISSN: 2169-3536. DOI: 10.1109/ACCESS.2021.3063316. URL: https://ieeexplore.ieee.org/document/9366730 (visited on 02/24/2025).

[209] Jennifer Leijon and Cecilia Boström. "Charging Electric Vehicles Today and in the Future". en. In: *World Electric Vehicle Journal* 13.8 (Aug. 2022), p. 139. ISSN: 2032-6653. DOI: 10.3390/wevj13080139. URL: https://www.mdpi.com/2032-6653/13/8/139 (visited on 02/12/2025).

[210] Tomislav Erdelić and Tonči Carić. "A Survey on the Electric Vehicle Routing Problem: Variants and Solution Approaches". en. In: *Journal of Advanced Transportation* 2019.1 (2019), p. 5075671. ISSN: 2042-3195. DOI: 10.1155/2019/5075671. URL: https://onlinelibrary.wiley.com/doi/abs/10.1155/2019/5075671 (visited on 02/12/2025).

[211] Martin Lindberg and Jennifer Leijon. "Effects on Airport Operations from a New Regional Electric Flight Network in Northern Scandinavia". In: *2024 IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC)*. Nov. 2024, pp. 1–6. DOI: 10.1109/ESARS-ITEC60450.2024.10819765. URL: https://ieeexplore.ieee.org/document/10819765/?arnumber=10819765 (visited on 02/12/2025).

[212] 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". en. In: *Transportation Research Part C: Emerging Technologies* 155 (Oct. 2023), p. 104313. ISSN: 0968090X. DOI: 10.1016/j.trc.2023.104313. URL: https://linkinghub.elsevier.com/retrieve/pii/S0968090X23003029 (visited on 02/13/2025).

[213] U. Sultana et al. "Placement and sizing of multiple distributed generation and battery swapping stations using grasshopper optimizer algorithm". In: *Energy* 165 (Dec. 2018), pp. 408–421. ISSN: 0360-5442. DOI: 10.1016/j.energy.2018.09.083. URL: https://www.sciencedirect.com/science/article/pii/S0360544218318474 (visited on 02/18/2025).

[214] Omer Burak Kınay, Fatma Gzara, and Sibel A. Alumur. "Full cover charging station location problem with routing". In: *Transportation Research Part B: Methodological* 144 (Feb. 2021), pp. 1–22. ISSN: 0191-2615. DOI: `10.1016/j.trb.2020.12.001`. URL: `https://www.science direct.com/science/article/pii/S0191261520304434` (visited on 02/12/2025).

[215] Francesco Salucci et al. "An optimization Model for Airport Infrastructures in Support to Electric Aircraft". In: *2019 IEEE Milan PowerTech*. June 2019, pp. 1–5. DOI: `10.1109/PTC.2019.8 810713`. URL: `https://ieeexplore.ieee.org/abstract/document/8810713` (visited on 02/11/2025).

[216] Cedric Y. Justin et al. "Power optimized battery swap and recharge strategies for electric aircraft operations". In: *Transportation Research Part C: Emerging Technologies* 115 (June 2020), p. 102605. ISSN: 0968-090X. DOI: `10.1016/j.trc.2020.02.027`. URL: `https://www.sciencedirect.com/science/article/pii/S0968090X19310241` (visited on 02/11/2025).

[217] Alan Kinene et al. "Electric aircraft charging network design for regional routes: A novel mathematical formulation and kernel search heuristic". In: *European Journal of Operational Research* 309.3 (Sept. 2023), pp. 1300–1315. ISSN: 0377-2217. DOI: `10.1016/j.ejor.2023.02.006`. URL: `https://www.sciencedirect.com/science/article/pii/S037722172300125X` (visited on 02/09/2025).

[218] Ben Chan et al. "Optimizing fleet assignment decisions for regional airlines with hybrid electric aircraft uptake". In: (Sept. 2024).

[219] Mihaela Mitici, Madalena Pereira, and Fabrizio Oliviero. "Electric flight scheduling with battery-charging and battery-swapping opportunities". en. In: *EURO Journal on Transportation and Logistics* 11 (2022), p. 100074. ISSN: 21924376. DOI: `10.1016/j.ejtl.2022.100074`. URL: `https://linkinghub.elsevier.com/retrieve/pii/S2192437622000036` (visited on 02/11/2025).

[220] Chaug-Ing Hsu and Wei-Yin Eie. "Airline network design and adjustment in response to fluctuation in jet fuel prices". In: *Mathematical and Computer Modelling* 58.11 (Dec. 2013), pp. 1791–1803. ISSN: 0895-7177. DOI: `10.1016/j.mcm.2013.04.005`. URL: `https://www.sciencedire ct.com/science/article/pii/S0895717713001751` (visited on 02/11/2025).

[221] IATA. *Unveiling the biggest airline costs*. en. IATA Knowledge Hub. June 2024. URL: `https://www.iata.org/en/publications/newsletters/iata-knowledge-hub/unveiling-the-biggest-airline-costs/` (visited on 03/12/2025).

[222] David A. Dobbs. *Aviation Industry Performance: a review of the aviation industry in 2008*. May 2009.

[223] Philip G. Gayle and Ying Lin. "Cost pass-through in commercial aviation: theory and evidence". In: *Economic Inquiry* 59.2 (Apr. 2021), pp. 803–828. ISSN: 0095-2583, 1465-7295. DOI: `10.1111/ecin.12949`. URL: `https://onlinelibrary.wiley.com/doi/10.1111/ecin.12949` (visited on 03/12/2025).

[224] International Civil Aviation Organization. *Annual report of the council*. Tech. rep. Doc 9916. 2008.

[225] Megan Smirti Ryerson and Mark Hansen. "The potential of turboprops for reducing aviation fuel consumption". In: *Transportation Research Part D: Transport and Environment* 15.6 (Aug. 2010), pp. 305–314. ISSN: 1361-9209. DOI: `10.1016/j.trd.2010.03.003`. URL: `https://www.sciencedirect.com/science/article/pii/S1361920910000349` (visited on 03/12/2025).

[226] Chartchai Leenawong and Amarita Ritthipakdee. "Fuel Costs Optimization for Long-Haul Flight with Refueling Layovers". en. In: *International Journal of Technology* 15.6 (Dec. 2024), p. 1602. ISSN: 2087-2100, 2086-9614. DOI: `10.14716/ijtech.v15i6.7285`. URL: `https://ijtech.eng.ui.ac.id/article/view/7285` (visited on 02/27/2025).

[227] Ali Kheraie and Hani Mahmassani. "(PDF) Leveraging Fuel Cost Differences in Aircraft Routing by Considering Fuel Ferrying Strategies". In: *ResearchGate* (Oct. 2024). DOI: `10.3141/2300-16`. URL: `https://www.researchgate.net/publication/256083018_Leveraging_Fuel_Cost_Differences_in_Aircraft_Routing_by_Considering_Fuel_Ferrying_Strategies` (visited on 02/24/2025).