Integrated Flight Scheduling and Routing of Hybrid and Electric Aircraft: Enhancing Network Performance through Partial Recharging

Aerospace Engineering Thesis

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Integrated Flight Scheduling and Routing of Hybrid and Electric Aircraft: Enhancing Network Performance through Partial Recharging

by

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Scientific Paper

Integrated Flight Scheduling and Routing of Hybrid and Electric Aircraft: Enhancing Network Performance through Partial Recharging

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The aviation industry continues to grow at a steady annual rate of approximately 4.4%, intensifying global environmental concerns in light of international climate goals. In response, airlines are under increasing pressure to adopt sustainable innovations, with electrified aviation emerging as a promising pathway. One of the main challenges in electrified aviation is planning profitable flight schedules despite long turnaround times for battery recharging. To address this, a Flight Scheduling and Electrified Aircraft Routing (FSEAR) model was developed, advancing beyond models assuming full recharging or battery swaps. It integrates partial recharging through a recursive three-dimensional time-space-energy dynamic programming framework, combining multi-label dominance on profit and energy with a CO_2 tax penalty for climate optimization. Based on the KLM Cityhopper network, three case studies with varying demand and distance profiles were developed. Results show that partial recharging increases profit by 22.5% to 27.8% compared to limiting operations to full recharging constraints. Emission reductions of 45.1% and 48.9% were achieved in close-range cases, while the long-range case showed a modest increase of 4.66%, reflecting a trade-off for enabling more profitable operations with higher flight frequency and greater demand coverage. A consistent reduction in fleet size and a shift to fully all-electric compositions were also observed. This study demonstrates that partial recharging significantly enhances both the operational efficiency and environmental performance of electrified aviation, supporting lower-emission fleet compositions and enabling a more sustainable, cost-effective alternative to regional air transport.

Nomenclature

Latin Symbols

a	=	Scaling constant	$(\sim)$
b	=	Elasticity constant	$(\sim)$
c	=	Cost	(€)
c	=	Fixed base fare constant	$(\sim)$
d	=	Day	$(\sim)$
d	=	Distance	(km)
E	=	Energy balance	$(\sim)$
e	=	Carbon di-oxide emission	(ton)
f	=	Speed fraction	$(\sim)$
f	=	Variation factor	$(\sim)$
$\mathbf{G}$	=	Set of ground arcs	$(\sim)$
$\mathcal{J}$	=	Objective value	$(\sim)$
$\mathbf{K}$	=	Set of aircraft types	$(\sim)$
$\mathbf{N}$	=	Set of airports	$(\sim)$
$\mathbf{R}$	=	Set of routes	$(\sim)$
R	=	Range	(km)
r	=	Normalized recharging rate	$(\sim)$
s	=	Number of seats	$(\sim)$
$\mathbf{T}$	=	Set of time steps	$(\sim)$
T	=	Time window	$(\sim)$
t	=	Time	(s)
v	=	Cruise velocity	(m/s)

Superscripts & Subscripts

arc	=	Individual arc
battery	=	Battery component
bow	=	Begin of week
cons	=	Consumption
cumul	=	Cumulative
elec	=	Electricity component
eow	=	End of week
fixed	=	Fixed component
FL	=	Flight
fuel	=	Fuel component
g	=	Ground arc
i	=	Departure airport index
j	=	Arrival airport index
k	=	Aircraft type
l	=	Flight arc

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leg	=	Flight leg
max	=	Maximum
new	=	New state
old	=	Old state
own	=	Ownership
P	=	Preferred
r	=	Route
rec	=	Recharging
recharge	=	Recharging component
rem	=	Remaining
req	=	Required
res	=	Resource
s	=	Sensitivity
s	=	Served
tot	=	Total

Abbreviations

2D	=	Two-dimensional
3D	=	Three-dimensional
AC	=	Number of Aircraft
AD	=	Aircraft Design
AEA	=	All-electric Aircraft
AS	=	Assumption
BM	=	Basic Airline Planning Model
CA	=	Conventional Aircraft
CC-CV	=	Constant-Current Constant-Voltage
CO	=	Climate Optimization
CS	=	Case Study
DP	=	Dynamic Programming
EATS	=	European Airport Traffic Statistics
EI	=	Emission Index
FL	=	Flight Action
FSEAR	=	Flight Scheduling & Electrified Aircraft Routing
GRD	=	Ground Action
HEA	=	Hybrid-electric Aircraft
IATA	=	International Air Transport Association
ICAO	=	International Civil Aviation Organization
LF	=	Load Factor
LTO	=	Landing and Take-Off
MCC	=	Multi-stage Constant-Current
MILP	=	Mixed-Integer Linear Programming
MTOM	=	Maximum Take-Off Mass
OD	=	Origin Destination
PR	=	Partial Recharging
RE	=	Requirement
RPK	=	Revenue Passenger Kilometer
SOC	=	State of Charge
TAT	=	Turnaround Time
TATF	=	Turnaround Time Factor
TZ	=	Time Zone
UTC	=	Universal Time Coordinated

Chemical Symbols

CO_2	=	Carbon di-oxide

I. Introduction and Literature Review

The aviation industry has steadily grown over the past decades, with projected annual growth rates of 4.4 % [1–3]. Despite a temporary drop in CO_2 emissions during the COVID-19 pandemic, emissions have since returned to pre-pandemic levels [2, 4]. As traffic is expected to continue growing [2, 3], the sectors environmental impact remains a critical concern. In response, global initiatives like the *Paris Agreement* [5] and sector-specific goals such as *NASA N+i* and *Fly The Green Deal* [6, 7] underscore the need for emissions reduction. Electrified aircraft, both all-electric (AEA) and hybrid-electric (HEA), have emerged as promising solutions for decarbonization [8–10], with battery and energy strategies playing a central role [4, 11, 12].

Key enablers of electrified aviation include aircraft design, performance optimization, and battery technology [4, 8, 13–16]. Electrified aircraft design, defined by the degree of hybridization, strongly influences network performance [17]. Optimization of mission profiles and in-flight energy use improves climate impact [18, 19], while battery design directly affects operational range and recharging strategies. More efficient recharging strategies, such as boost charging and Multi-stage Constant-Current (MCC) charging, have been proposed as alternatives to conventional Constant-Current Constant-Voltage (CC-CV) charging [4, 20, 21].

In parallel, operational aspects of electrified aviation are crucial to airline network performance [10, 22]. Airline planning, primarily flight scheduling and aircraft routing, is essential for achieving operational efficiency [23]. Over the past decades, optimization techniques such as mixed-integer linear programming (MILP) and dynamic programming (DP) have enhanced conventional aircraft (CA) performance. Models have incorporated features like passenger choice [24], spill cost and recapture [25], time flexibility [26, 27], and variable cruise velocity [13, 28]. Many studies also demonstrate the benefits of integrating flight scheduling and aircraft routing to improve overall network performance [29].

Integrating aircraft design and performance with operations offers major opportunities to enhance network performance [30–35]. Studies have shown promising results when airline planning is combined with either climate optimization or aircraft design [10, 14, 22]. While some research has integrated all three disciplines, incorporating partial recharging is now emerging as a key step toward making electrified aviation a viable alternative to conventional aviation [8]. This advancement enables a fully integrated system combining airline planning, partial recharging, climate optimization, and aircraft design. A visual overview of the interrelationships among these disciplines is shown in Figure 1.

In pursuit of climate-optimized airline operations, *Justin et al.* [10] proposed a hybrid half-itinerary half-leg MILP model using a hierarchical multi-objective trade-off between airline profitability and aircraft emissions. This approach expanded upon the earlier attempts of *Safak et al.* [28] and *Ma et al.* [36], which had failed to fully integrate new climate optimized airline operations.

The integration of airline planning and aircraft design has been widely studied, particularly for conventional aircraft. *Taylor & De Weck* [30] introduced a framework for jointly optimizing aircraft design and network flow, demonstrating a possible 10 % cost reduction. *Jansen & Perez* extended this by developing a series of frameworks that coupled fleet network allocation with conventional aircraft design [31–35]. Their work addressed objectives such as fuel-burn minimization, demand uncertainty, and multi-market planning, and highlighted the cost benefits of integrated design and planning.

More recently, attention has shifted toward all-electric and hybrid-electric aircraft. *Weit et al.* [37] optimized network operations and hybrid-electric aircraft design using the hybridization ratio as a key parameter, showing profit gains through payload and battery adjustments. A series of studies at Delft University of Technology further advanced these ideas. *Zuijderwijk* [15] developed a framework linking airline planning with electrified aircraft design, while *Scheers*[14] introduced a climate-optimized hybrid-electric design integrated into planning. Most recently, *Antunes* [13] extended this framework by accounting for the off-design performance of hybrid-electric aircraft, reinforcing the benefits of synchronized planning and design in future electric aviation.

While integrated electrified operations and aircraft design have progressed, battery recharging remains a critical next step for operational viability. Despite its importance, research on integrating recharging into flight scheduling and fleet assignment remains relatively scarce. Three notable studies have explicitly modeled the battery state of charge (SOC). In 2022, *Mitici & Pereira* [38] introduced a two-phase optimization framework for scheduling flights and recharging (or swapping), using a bilinear charging profile. In 2023, *Vehlhaber & Salazar* [39] embedded SOC progression into an all-electric fleet assignment and routing model, treating time intervals as charging or discharging. In 2024, *Kinene & Birolini* [40] proposed a bi-objective MILP within a three-dimensional (3D) time-space-energy network, distinguishing flight, ground, and recharging arcs to model battery dynamics.

Building on the idea that airline planning, aircraft design, and climate optimization can be unified, *Hoogreef et al.* [22] demonstrated that this integration achieves substantial emission reductions with only minor profit decreases. Their iterative methodology coupled fleet and network allocation with aircraft design, evaluated off-design conditions, and applied a climate optimization module, reinforcing the benefits of fully integrated aviation planning.

The reviewed literature reveals a research gap in integrating airline planning with partial recharging, climate optimization, and electrified aircraft design (highlighted in orange in Figure 1). This study addresses a substantial part of this gap by analyzing the impact of partial recharging strategies on airline network performance through optimized integration of flight scheduling and aircraft routing, while simultaneously maximizing profitability, reducing carbon emissions, and meeting operational constraints. Although electrified aircraft design is identified as part of the broader research gap, it is beyond the scope of this study. Accordingly, the following research question is posed:

> *What is the effect of incorporating partial recharging strategies into flight scheduling and aircraft routing on airline network profitability and carbon emission reduction?*

This paper introduces an iterative decision-making approach to generate suboptimal flight schedules and aircraft routes that maximize overall network performance. The approach uses a three-dimensional time-space-energy recursive dynamic programming model to compute suboptimal flight routes for all-electric and hybrid-electric aircraft under partial recharging. Financial profit is maximized while carbon emissions are penalized, The proposed methodology is applied to a case study to demonstrate its practical applicability and to capture the operational nuances of electrified airline networks, quantitatively evaluating the impact of partial recharging on network profitability and carbon emission.

This paper first presents the theoretical methodology in Section II, detailing the models structure and functionality. Section III then demonstrates the models applicability through a case study and performance verification. The results and corresponding sensitivity analysis are presented in Section IV, followed by key findings and future research recommendations in Section V.

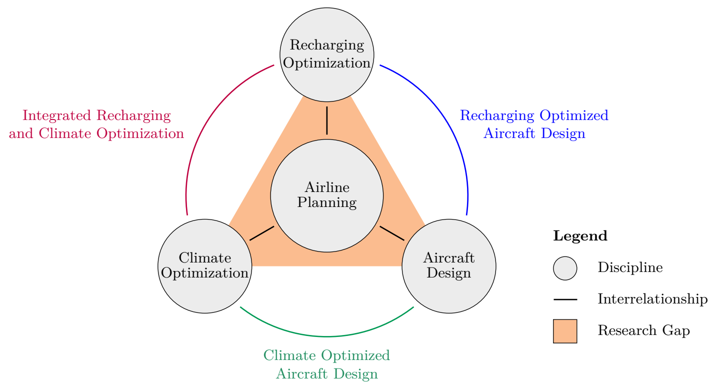


Figure 1 Schematic overview of the research disciplines, their interrelations, and the identified research gap

II. Methodology

The Flight Scheduling and Electrified Aircraft Routing (FSEAR) model is developed to enhance electrified airline network performance by explicitly integrating partial recharging strategies into the scheduling and routing process. This integration enables the model to capture key operational constraints more realistically, such as limited turnaround time (TAT), and to differentiate between the performance characteristics of hybrid-electric and fully electric aircraft, including their unique charging profiles. A core element of the model is the recursive three-dimensional dynamic programming algorithm, across time, space, and energy state, which allows for the detailed modeling of energy usage and partial recharging throughout the network. Dynamic programming is chosen over traditional MILP-based formulations due to its flexibility in accommodating nonlinear charging profiles, its inherently decision-based structure, and its ability to prune the solution space recursively, eliminating the need for exhaustive search. A multi-label dominance approach is implemented to manage complexity, allowing efficient exploration of promising paths with consistent decision logic. Unlike MILP solutions that typically approach global optimality, the DP-based FSEAR model yields suboptimal but feasible solutions within a tractable computational framework. In addition to operational performance, the model incorporates climate objectives by penalizing carbon emissions, thereby supporting sustainable and economically viable electrified operations.

The FSEAR model operates through an iterative decision-making process, illustrated in Figure 2. The process begins with data initialization and preprocessing, after which the *Aircraft Selection Module* is activated. This module identifies the aircraft type whose corresponding route yields the highest profit. It includes a series of sub-modules executed for each aircraft type in the fleet: *Demand Processor*, *Network Creation*, and *Path Explorer*. These sub-modules generate the most profitable suboptimal route for each aircraft type. A profitability check follows to confirm that assigning the aircraft yields a positive return. If valid, the served portion of demand is removed from the overall demand pool. A second check determines whether all demand has been satisfied. If not, the *Aircraft Selection Module* is re-invoked to allocate further aircraft and routes. If all demand is served or no further profitable assignments remain, the algorithm terminates, producing the final solution.

This sequential, priority-based aircraft assignment introduces a structural source of suboptimality. Aircraft are selected one at a time based on the highest individual profit, without jointly evaluating the broader fleet configuration. As a result, early decisions are made without considering their impact on the feasibility and efficiency of subsequent assignments. Although this reduces computational burden, it limits exploration of a more balanced fleet deployment across the network.

This methodology section begins by introducing the model environment in Section II.A. The following subsections describe the individual modules of the FSEAR model. The modeling of demand within the FSEAR framework is presented in Section II.B, followed by a description of the *Network Creation* module and the formulation of the objective function in Sections II.C and II.D, respectively. Finally, based on the information provided by these modules, the three-dimensional dynamic programming *Path Explorer* is detailed in Section II.E.

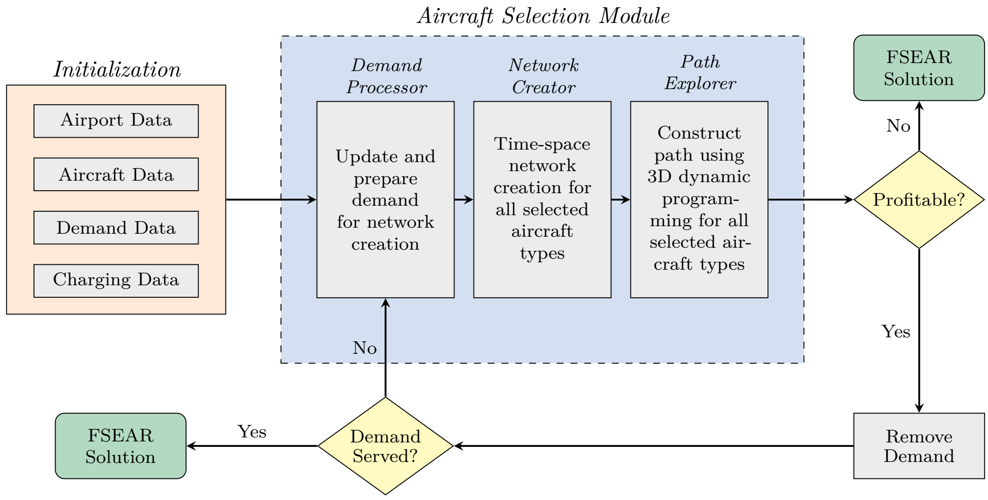


Figure 2 Schematic flowchart of the FSEAR model structure and process flow

A. Model Environment

The FSEAR model adheres to a set of predefined requirements and operates under a set of assumptions. These elements define the model's design space and operational constraints. The model requirements and assumptions are provided in Sections II.A.1 and II.A.2, respectively.

1. Requirements

The theoretical methodology is guided by key requirements that ensure the FSEAR model addresses operational, economic, and environmental objectives. Each requirement is assigned a unique identifier, prefixed by RE-, followed by a two-letter code indicating its category: BM (Basic Airline Planning Model), PR (Partial Recharging), CO (Climate Optimization), and AD (Aircraft Design). A comprehensive overview of the key model requirements is presented in Table 1.

Table 1 Key FSEAR model requirements

Code	**Description**
RE-BM-01	The model shall maximize airline financial profit as its main objective.
RE-BM-02	All aircraft shall adhere to a minimum ground time equal to the minimum turnaround time (TAT), allowing for off-boarding, on-boarding, and other ground operations.
RE-BM-03	All aircraft assigned to a flight leg shall belong to the fleet of available aircraft types.
RE-BM-04	The model shall only consider profitable routes consisting of a set of flight legs to be operated (an individual flight leg does not need to be profitable).
RE-BM-05	The model shall account for the hourly distribution of passenger demand for each origin-destination (OD) pair.
RE-PR-01	Electrified aircraft batteries do not have to be fully recharged before departure.
RE-PR-02	All aircraft shall recharge during parking at an airport, unless the state of charge (SOC) is already at 100 %.
RE-PR-03	All hybrid-electric aircraft shall refuel the required amount, in addition to battery recharging, to satisfy range requirements for the next flight.
RE-CO-01	The model shall financially penalize CO_2 emissions from flight operations by means of emission tax.

2. Assumptions

The model relies on assumptions that ensure feasibility, applicability, and computational efficiency. These assumptions define the operational conditions and constraints under which the model performs. Each assumption is assigned a unique identifier using the same structure as the model requirements. A comprehensive overview of the key model assumptions is presented in Table 2.

Table 2 Key FSEAR model assumptions

Code	Description
AS-BM-01	A single day of operations is discretized into time intervals of 10 minutes from 06:00 to 22:00.
AS-BM-02	Passenger demand for itineraries is discretized in constant one-hour intervals.
AS-BM-03	Aircraft overnight parking is possible at each airport with corresponding overnight parking fee.
AS-BM-04	The electricity price is 0.1545 €/kWh.[a]
AS-BM-05	The fuel price is 0.538 €/kg.[b]
AS-BM-06	The CO_2 emission index (EI) of fuel is 3.16 kg CO_2/kg fuel.[41]
AS-BM-07	The CO_2 emission index of electricity is 0.03 kg CO_2/kWh.[c]
AS-PR-01	All airports have battery recharging and conventional refueling facilities suitable for every aircraft in the airline fleet.
AS-PR-02	The energy price for recharging at airports is considered equal across all airports.
AS-PR-03	Airports have sufficient energy power supply to recharge any number of aircraft simultaneously.
AS-CO-01	The financial cost penalty for CO_2 emission is equal for all European Union countries and is set at 75 €/ton CO_2.[d]

[a] `https://ec.europa.eu/eurostat/databrowser/view/nrg_pc_205/default/table?lang=en` [Accessed: 2025-02-26]
[b] `https://jet-a1-fuel.com/price/netherlands-the` [Accessed: 2025-02-26]
[c] `https://www.eea.europa.eu/en/analysis/indicators/greenhouse-gas-emission-intensity-of-1?utm_source=chatgpt.com` [Accessed: 2025-04-24]
[d] `https://ember-energy.org/data/european-electricity-prices-and-costs` [Accessed: 2025-02-26]

B. Demand Processing

Following data initialization, the demand is further processed to align with FSEAR model requirements. This processing involves three key steps. First, the total daily demand is disaggregated into a time-dependent format to reflect temporal variations in passenger preferences, as described in Section II.B.1. Second, during network creation, time-resolved demand is mapped to feasible flight legs, accounting for departure time flexibility and avoiding duplicate assignments, as detailed in Section II.B.2. Finally, after flight selection, served demand is removed using a greedy algorithm, and remaining demand is updated. This introduces trade-offs in demand tracking and assignment order, further discussed in Section II.B.2.

1. Demand Distribution

Passenger demand is defined as origin-destination (OD) pairs, each associated with a total daily volume. To reflect temporal variation in travel preferences, this daily demand is distributed over the operational day using a predefined hourly profile. Each profile is normalized such that hourly proportions sum to one, preserving total demand. A bimodal Gaussian mixture with a constant baseline, capturing typical morning and evening peaks, is used to define these profiles, as illustrated in Figure 3. The resulting time-dependent directional demand function enables the model to account for hourly variations during flight leg evaluation.

2. Demand Assignment and Removal

The disaggregated demand distribution is combined with a generalized assumption regarding passenger flexibility in departure time. Passengers with a preferred departure hour T_P are assumed to also accept flights departing at T_{P-2}, T_{P-1}, and T_{P+1}. This assumption creates a modeling challenge because overlapping time windows can lead to the same passengers being assigned multiple times. To prevent this, a dynamic tracking mechanism is used that records which flight legs have already drawn demand from each hour and OD pair. This ensures that only the actual remaining demand is available in later assignments. The time-window assignment logic is illustrated in Figure 4.

However, even with this tracking mechanism, the use of time windows introduces a structural source of suboptimality. The dynamic programming algorithm builds flight paths recursively through locally optimal decisions at each state, but drawing demand from various time windows can reduce its availability for subsequent paths. As a result, early assignments may restrict later flexibility, leading to suboptimal overall outcomes despite individually justified decisions.

A second source of suboptimality stems from the greedy algorithm used for demand removal. After a flight leg is selected, the algorithm first assigns demand from the preferred hour T_P, then from the adjacent hours T_{P-1} and T_{P+1}, and finally from T_{P-2} if needed. While this simplifies implementation, it does not optimize which portion of the time window demand is used. A more advanced approach would require additional decision variables to explicitly manage demand allocation, which would increase model complexity and computational burden. Therefore, the greedy strategy is adopted as a practical balance between fidelity and tractability.

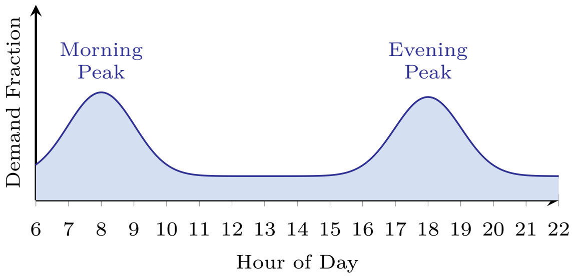


Figure 3 Normalized hourly demand distribution based on a bimodal Gaussian mixture with a constant baseline for an operational day (06:00 - 22:00)

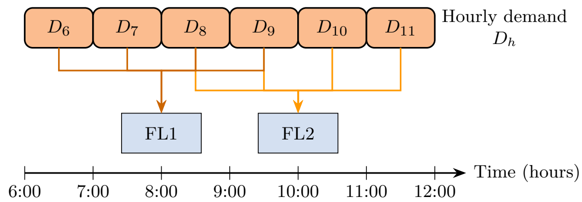


Figure 4 Illustration of time-window-based demand allocation for two flight legs (FL1 and FL2) departing at different hours, showing overlapping retrieval from shared hourly demand pools

C. Network Creator

Before executing the *Path Explorer*, a directed time-space network is constructed for each aircraft type under consideration, as illustrated in Figure 5. This framework enables generation of all feasible flight routes across a defined time horizon by integrating both spatial and temporal dimensions. The network consists of nodes and arcs. Nodes represent discrete states defined by a specific airport and time step, while arcs denote transitions between these states. Ground arcs connect nodes at the same airport over time, representing parking or other ground operations. Flight arcs capture movement between airports and typically span several time steps. This structure supports detailed modeling of operational constraints across both space and time. To account for time zone differences, all local time steps are standardized using the Universal Time Coordinated (UTC) offset of each airport.

The operational day is defined by a fixed start and end time and is discretized into fixed time intervals. A time-space network is then generated for each aircraft type $k \in \mathbf{K}$, containing all nodes for each airport $n \in \mathbf{N}$ and time step $t \in \mathbf{T}$, along with feasible arcs connecting them. Arcs are created based on the sum of flight time and TAT for type k, linking to the nearest feasible future node while accounting for spare time. Only arcs that satisfy the operational constraints are included. A flight arc is feasible if it adheres to the range and temporal feasibility constraints defined in Equations (1) and (2). The range constraint ensures the aircraft's range (R^k) the covers the leg distance (d_{ij}), while the temporal constraint ensures that the arrival time does not exceed the final time step T. Flight time consists of a fixed landing and take-off (LTO) duration and a cruise phase, with the latter based on the cruise velocity v^k of aircraft type k. As shown in Equation (2), part of the total distance is allocated to the LTO phase t_{LTO}, estimated using a speed fraction f_{LTO}, and the remaining distance is operated at cruise speed. Based on these calculations, flight arcs are assigned relevant parameters and matched with time-dependent demand as modeled in Section II.B.

$$d_{ij} \leq R^k, \qquad \forall i, j \in \mathbf{N}, \quad i \neq j, \qquad \forall k \in \mathbf{K} \tag{1}$$

$$t + \left[t_{\text{LTO}} + \underbrace{\frac{d_{ij} - v^k \cdot f_{\text{LTO}} \cdot t_{\text{LTO}}}{v^k}}_{\text{Cruise time}} + \text{TAT}^k \right] \leq T, \qquad \forall i, j \in \mathbf{N},\ i \neq j,\ \forall t \in \mathbf{T},\ \forall k \in \mathbf{K} \tag{2}$$

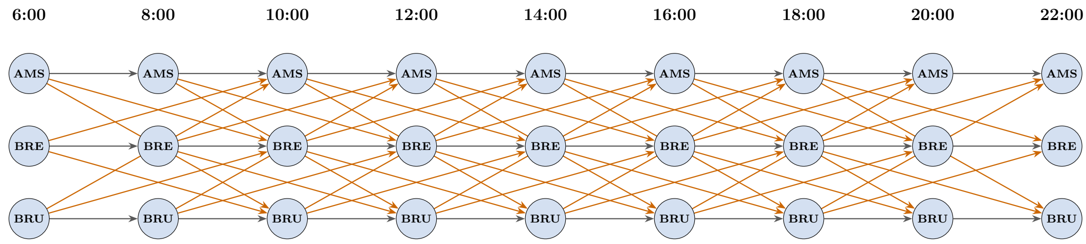


Figure 5 Schematic time-space network for three airports (AMS, BRE, BRU) using a two-hour interval, illustrating ground arcs (gray) and flight arcs (orange)

D. Objective Function

The model aims to maximize total profit by efficiently scheduling and assigning aircraft to meet passenger demand. The objective function combines a system-level and a flight leg-level component by summing the objective values of all selected routes $r \in \mathbf{R}$, each comprising a set of flight arcs $l \in \mathbf{L}_r$ and ground arcs $g \in \mathbf{G}_r$, while subtracting the ownership costs of the assigned fleet. The total objective value ($\mathcal{J}$), defined in Equation (3), includes profits from all flight legs ($\mathcal{J}^l_{\text{leg}}$) and ground operations ($\mathcal{J}^g_{\text{ground}}$), including parking and overnight charges. Ownership costs are based on the number of aircraft per type (AC^k) and their annual lease-based unit cost (c^k_{own}), as detailed in Section II.D.4. The flight leg objective function in Equation (4) consists of revenue, operating cost, and emission tax terms, further detailed in Sections II.D.1 to II.D.3.

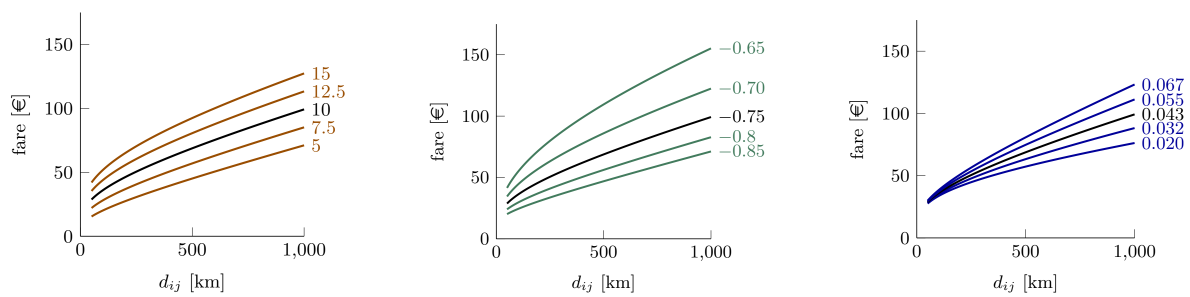
$$\max \mathcal{J} = \sum_{r\in\mathbf{R}} \left[\sum_{l\in\mathbf{L}_r} \mathcal{J}^l_{\text{leg}} + \sum_{g\in\mathbf{G}_r} \mathcal{J}^g_{\text{ground}} \right] - \sum_{k\in\mathbf{K}} c^k_{\text{own}} \cdot \text{AC}^k \tag{3}$$

$$\mathcal{J}^l_{\text{leg}} = \underbrace{\text{fare}^l_{ij} \cdot s^k \cdot \text{LF}^l}_{\text{Revenue}} - \underbrace{\left(c^k_{\text{fixed}} + c^l_{\text{fuel}} + c^l_{\text{battery}}\right)}_{\text{Operational Costs}} - \underbrace{c_{\text{emission}} \cdot e^l}_{\text{Emission Tax}} \tag{4}$$

1. Revenue

Revenue is based on a fare that depends on the great-circle distance (d_{ij}) between the origin and destination airports i and j, and the number of transported passengers, given by the load factor (LF) multiplied by the seat capacity (s^k) of aircraft type k. A distance-based yield model is used to reflect realistic airline pricing behavior. The fare (fare_{ij}) is computed using Equation (5), which includes a scaling coefficient (a), an elasticity exponent (b), and a fixed base fare (c). This formulation captures the typical decline in per-kilometer yield on longer flights, while ensuring cost recovery via the base fare. The effect of varying each parameter (a, b, and c) on the fare-distance relationship is illustrated in the three subfigures in Figure 6.

$$\text{fare}_{ij} = \left(a \cdot d^b_{ij} + c\right) \cdot d_{ij} \tag{5}$$



(a) Varying scaling coefficient a **(b)** Varying elasticity component b **(c)** Varying base fare constant c

Figure 6 Sensitivity of the fare function in Equation (5) to parameters a (a), b (b), and c (c), with all others held constant and each curve labeled by its parameter value while the baseline is shown in black

2. Operational Cost

Each flight leg incurs three operational cost components: the fixed operating cost c^k_{fixed} for aircraft type k, the fuel cost (c^l_{fuel}) and the battery cost (c^l_{battery}), based on the fuel and electric energy consumed on leg l. When on the ground, the aircraft incurs a fixed parking fee, with an additional charge if the stop includes an overnight period.

The fixed operating cost includes crew and airport-related charges. Crew costs are determined by the required number of crew members, annual wage rates, and the sum of flight and turnaround times, following *Antunes* [13] and *Proesmans* [42]. Airport costs comprise fixed fees for landing, parking, navigation, and handling, which remain constant across flight legs and do not depend on load or fuel use. Parking charges, including overnight fees, are indexed to aircraft's Maximum Take-Off Mass (MTOM) and airport size based on annual passenger volumes. A full overview of the cost input parameters is provided in Appendix B.

Fuel and battery costs are computed by multiplying consumption, measured in liters (fuel) and kilowatt-hours (kWh) (electricity), by their respective unit prices. Hybrid-electric aircraft incur both fuel and battery costs, while conventional aircraft rely solely on fuel, and all-electric aircraft incur only battery costs.

3. Emission Tax

Following *Antunes* [13], flight emissions are penalized via a CO_2 emission tax, which reduces the objective value of each flight leg. The emission tax is computed as the product of total CO_2 emissions and a fixed unit cost per ton. Total emissions are derived from both fuel and electricity consumption, each weighted by the respective emission factor for each energy source.

4. Cost of Aircraft Ownership

Due to the lack of standardized leasing data, particularly for all-electric and hybrid-electric aircraft types, this study adopts an established approximation method. The annual lease cost ($\text{CAQU}_{j,y}$) for aircraft type k in year y is estimated as a fixed fraction of the acquisition price (APP_j), following the approach of *Jansen & Perez* [34], as represented by Equation (6). An acquisition price uplift of 17 % for hybrid-electric and 20 % for fully electric aircraft is applied, based on *Finger et al.* [43] and *Antunes* [13]. An uniform annualization factor is applied across all aircraft types to ensure consistency.

$$\text{CAQU}_{k,y} = 0.0835 \cdot \text{APP}_k \tag{6}$$

E. Path Explorer

The *Path Explorer* module determines a suboptimal routing solution for a given aircraft type within the time-space network of feasible flight legs. It applies a three-dimensional recursive dynamic programming algorithm, by extending the conventional time-space structure with an additional energy balance dimension to form a time-space-energy network, as visualized in Figure 7. This added dimension captures the aircraft's available energy and ensures operational feasibility of each flight. Ground arcs represent either standard operations or recharging, depending on whether the aircraft is already fully recharged. Paths are constructed recursively, beginning at the end of the day and progressing backward. A multi-label objective framework tracks both cumulative objective value and energy balance, retaining only non-dominated solutions across these metrics.

The three-dimensional time-space-energy network is detailed in Section II.E.1, which explains the rationale for incorporating energy balance as a third dimension. Energy dynamics over arcs are detailed in Section II.E.2. The multi-label objective approach, including dominance criteria over profit and energy balance, is described in Section II.E.3. The boundary conditions guiding the optimization process are outlined in Section II.E.4. The complete algorithm is presented in Section II.E.5, integrating all preceding components. Lastly, Section II.E.6 describes the extension from daily suboptimal paths into a continuous weekly schedule.

1. Time-Space-Energy Network

The conventional two-dimensional time-space network is extended to a three-dimensional time-space-energy framework to represent the evolving energy state of electrified aircraft. Although prior studies such as *Kinene & Birolini* [40] incorporated battery SOC as a third dimension in a MILP framework, the recursive dynamic programming approach used in this study cannot directly model SOC, since its value is unknown during backward propagation.

Instead, this dimension is represented by an energy balance variable (E), denoting the fraction of battery capacity available to operate future flights. Energy depletion and recharging are applied dynamically through transitions along arcs, as further detailed in Section II.E.2. The normalized energy balance is defined as the complement of the normalized battery SOC, as shown in Equation (7).

$$E = 1 - \mathrm{SOC}, \quad E, \mathrm{SOC} \in [0, 1] \tag{7}$$

The rationale for adopting the energy balance variable stems from the backward nature of the dynamic programming algorithm. At each state, sufficient energy must be available not only for the immediate flight arc but also for subsequent arcs selected earlier in the optimization process. This requires recharging to be planned in advance, as insufficient energy at any state may restrict feasible paths and exclude more profitable routes. By structuring the optimization around the energy balance variable, the model dynamically allocates recharging opportunities, balance available turnaround time and airport energy infrastructure to maximize profitability while ensuring operational feasibility. Incorporating this third dimension thus provides the flexibility required for dynamic recharging strategies and enables the selection of profitable routes that satisfy energy constraints.

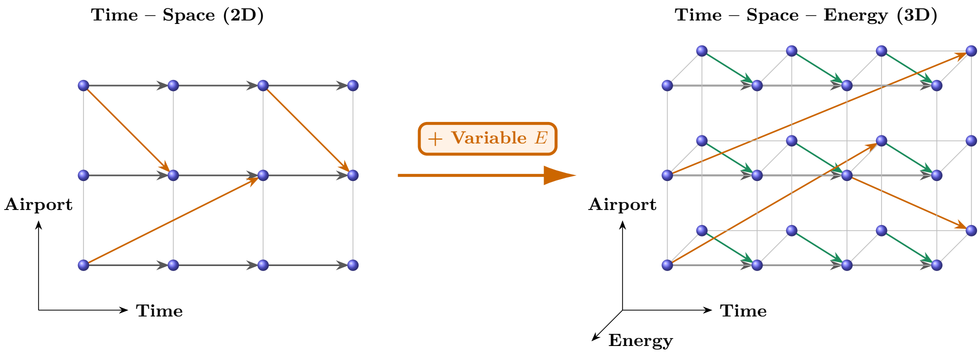


Figure 7 Conceptual transition from a time-space (2D) to a time-space-energy (3D) model by adding energy variable E, with flight arcs (orange), ground arcs (gray), and recharging arcs (green)

2. Energy Balance Change of Arcs

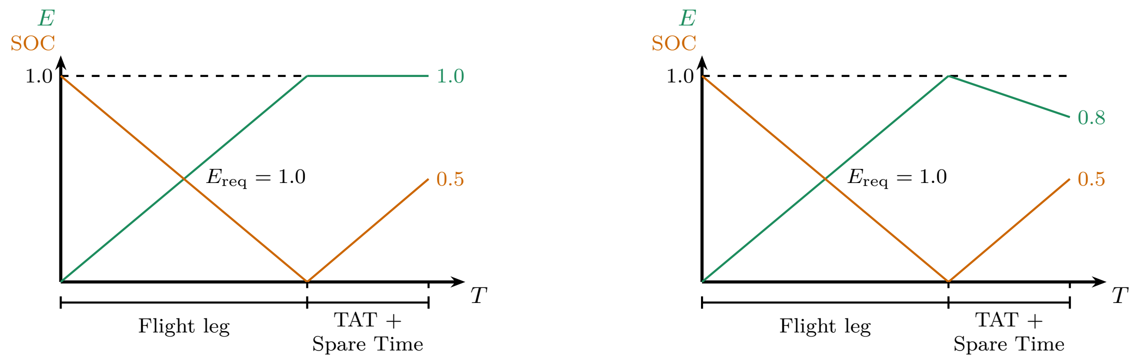
The energy balance evolves through two arc types that incorporate partial recharging: ground arcs and flight arcs. Ground arcs represent on-ground charging events, while flight arcs model both energy depletion from flight and potential partial recharging during turnaround and spare time.

Ground arcs result solely in recharging. During backward recursion of the dynamic programming process, they increase the energy balance. Recharging is computed based on a predefined charging strategy (linear, bilinear, or MCC) specific to the aircraft-airport combination and current energy state. The objective value for ground arcs is set to zero, as charging costs are already embedded in the flight arc costs.

Flight arcs lead to energy balance depletion while also allowing partial recharging. Their feasibility is evaluated by checking whether the current energy balance, combined with recharging during TAT and spare time, is sufficient to meet the energy requirement of the flight. Although TAT and spare time follow the flight in real-world operations, the backward structure of the dynamic programming formulation appear before the flight leg in the optimization process. As a result, recharging during these intervals does not contribute to the just-completed flight but ensures that sufficient energy is available for subsequent flights. A flight is considered feasible if the sum of the current energy balance and the energy recharged during TAT and spare time is sufficient for the flights energy requirement, without exceeding the batterys maximum capacity ($E_{\max}$). The total recharging time during the ground phase of a flight arc is determined by a turnaround time factor (TATF), which specifies the portion of TAT allocated to charging, along with the available spare time (t_{spare}). The recharging constraint ensures that the recharged energy (E_{recharge}) does not exceed $E_{\max}$, as defined in Equation (8). The recharging rate $r(\mathrm{SOC})$ depends on the current state of charge and the selected charging profile, which together govern the battery's charging speed over the available time. Since charging behavior is defined as a function of SOC, the normalized energy balance is internally converted to its corresponding SOC level to accurately evaluate the recharging rate $r(\text{SOC})$.

$$E_{\text{recharge}} = \min\left[E_{\max} - E, r(E) \cdot (\text{TAT} \cdot \text{TATF} + t_{\text{spare}})\right] \tag{8}$$

The dynamics of the recharging constraint are illustrated in Figure 8 and highlight reduced recharging during a flight arc's ground phase. Although a forward time propagation would allow a recharging increase of 0.5 in SOC, the backward recursive structure of the dynamic programming model limits the feasible recharged amount. Figures 8a and 8b present two scenarios. In the first, the full energy consumption results in no recharging (0.0), while in the second, an initial energy level of 0.8 allows only 0.2 to be recharged. In both cases, a total of 0.5 could have been recharged if the full available ground time were used in a forward-time formulation.

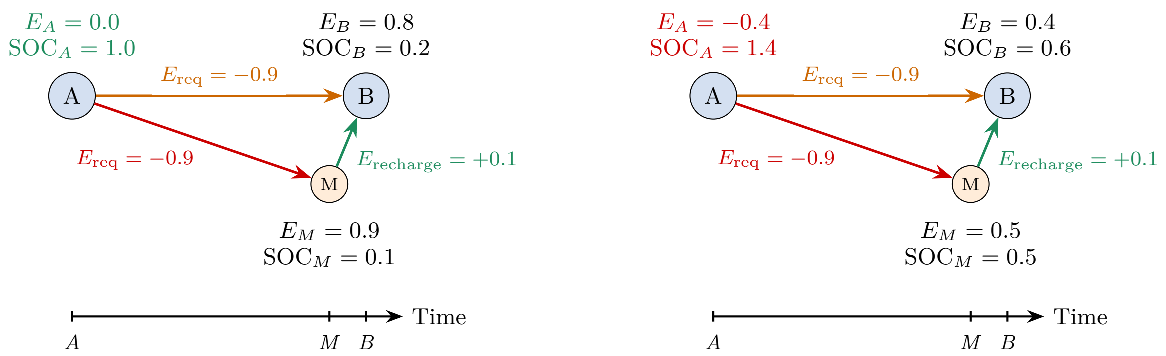


(a) Scenario of $E = 1.0$

(b) Scenario of $E = 0.8$

Figure 8 Energy variable E and SOC evolution during a flight leg followed by partial recharging under two different scenarios

The energy dynamics of flight arcs and their feasibility conditions are illustrated in Figures 9a and 9b, which depict two example scenarios using a fictitious intermediary node M. Although M does not physically exist in the network, it is introduced to conceptually separate the flight leg and the subsequent ground time (TAT and spare time), which together form a single flight arc. In this setup, the arc (A, M) models the flight operation, while (M, B) captures the on-ground recharging phase. Figure 9a illustrates a feasible scenario in which recharging during TAT and spare time allows the flight leg to be executed, even though the energy balance at node B (E_B) is initially below the required threshold. This results in valid values for both the energy balance and the corresponding SOC, indicated in green. In contrast, Figure 9b illustrates an infeasible scenario where the battery SOC exceeds its maximum capacity and the energy balance becomes negative, both violations indicated in red. While SOC evolves forward in time, the energy balance is propagated backward.



(a) Feasible flight arc

(b) Infeasible flight arc

Figure 9 Time-space visualization of a feasible (a) and an infeasible (b) flight arc, illustrating SOC (forward) and energy balance E (backward) propagation

3. Multi-Label Objective

The time-space-energy DP method employs a multi-label objective to track both the cumulative objective value and energy balance. Although the primary objective is to maximize profit, the algorithm must also preserve routes with higher remaining energy, which may enable more profitable decisions later in the schedule. To ensure efficient path selection and reduce computational complexity, a label dominance strategy is applied: a label $(\mathcal{J}_A, E_A)$ dominates another label $(\mathcal{J}_B, E_B)$ if and only if it satisfies the condition defined in Equation (9). This criterion discards suboptimal labels early while preserving promising paths that balance profitability and energy feasibility.

$$\mathcal{J}_A \geq \mathcal{J}_B \quad \wedge \quad E_A \geq E_B \tag{9}$$

4. Boundary Conditions

Two key boundary conditions are required in the DP model: one at the final time step (initial state of the backward recursion) and one at the start of the operational day (final state of the recursion). At the final time step T, all states are initialized, represented by Equation (10), with a cumulative profit of zero and an energy balance of $E_{\max}$, reflecting that no flights will be operated beyond this point and allowing full battery depletion. This setup enables the model to allocate all remaining energy without constraint. In contrast, no fixed conditions are imposed at the initial time step. The DP algorithm evaluates all possible final states by computing the resulting cumulative objective value and remaining energy balance.

$$(\mathcal{J}_T,\, E_T) = (0.0,\, 1.0) \tag{10}$$

5. Path Explorer Algorithm

The DP algorithm iterates through a structured sequence of steps, as visualized in Figure 10, and is organized around two decision stages. The final state is first initialized based on the boundary conditions in Section II.E.4. The algorithm then explores all nodes in the time-space-energy network. For each node, it evaluates all feasible arcs (flight and ground), applying the following steps:

1. *Arc Feasibility Check:* Assesses whether a flight arc is feasible for operation by the aircraft based on the current energy balance, as explained in Section II.E.2.
2. *Energy Balance Update:* Updates the energy balance by incorporating energy consumption and recharging, as detailed in Section II.E.2.
3. *Objective Determination:* Evaluates the arcs objective value based on relevant cost and revenue components, as outlined in Section II.D.

Once all arcs for a selected node have been evaluated, dominated labels are removed using the approach in Section II.E.3. This process is repeated until all nodes in the network have been explored. The optimal path is then reconstructed by tracing the stored arcs in each label, yielding the sequence of decisions that maximizes the cumulative objective value.

6. Weekly Path Construction

The weekly schedule is constructed by executing the daily *Path Explorer* recursively across seven consecutive days. Each day d builds upon the outcome of the previous evaluated day, as mathematically represented in Figure 11 and additionally described in the stepwise approach below:

1. *Initialization:* Day 7 is initialized at the base state with zero profit and full energy balance. For each subsequent day $d < 7$, the initial labels for the final time step at each airport are set to the end-of-day state (location, cumulative profit, and residual energy) computed by the previously evaluated day $d + 1$.
2. *Daily Exploration:* The *Path Explorer* is executed using backward dynamic programming to identify all non-dominated paths, characterized by cumulative objective value and energy balance, that terminate at each airport by the start of day d.
3. *Overnight Recharge and Cost:* For every candidate path at the begin-of-day state, the recharge module computes the overnight energy replenishment (applied until the previous days end-of-day state) and

the corresponding parking fee. Both values are incorporated into the cumulative objective, where the parking cost is subtracted, and the energy benefit is added.

4. *Selection:* At each airport, the dominance rule is reapplied to determine the set of non-dominated labels based on objective value and energy balance. These labels serve as the starting state for day $d-1$. In most cases, only a single label remains, as overnight recharging typically restores the energy balance to $E_{\max}$, making energy non-limiting and leaving profit as the sole dominance factor.
5. *Recursion:* The above steps are applied sequentially for $d = 7, \ldots, 1$, producing a sequence of daily solutions that, once concatenated, form a suboptimal weekly schedule.

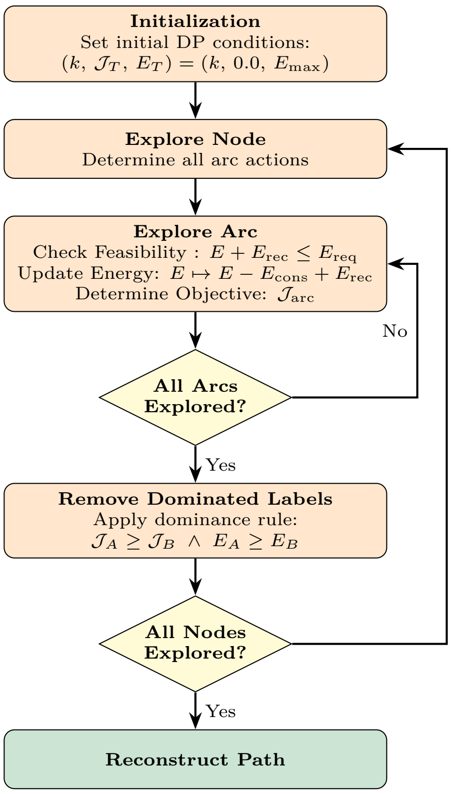


Figure 10 Flowchart of the *Path Explorer* algorithm, illustrating the recursive evaluation of flight paths in the time-space-energy network

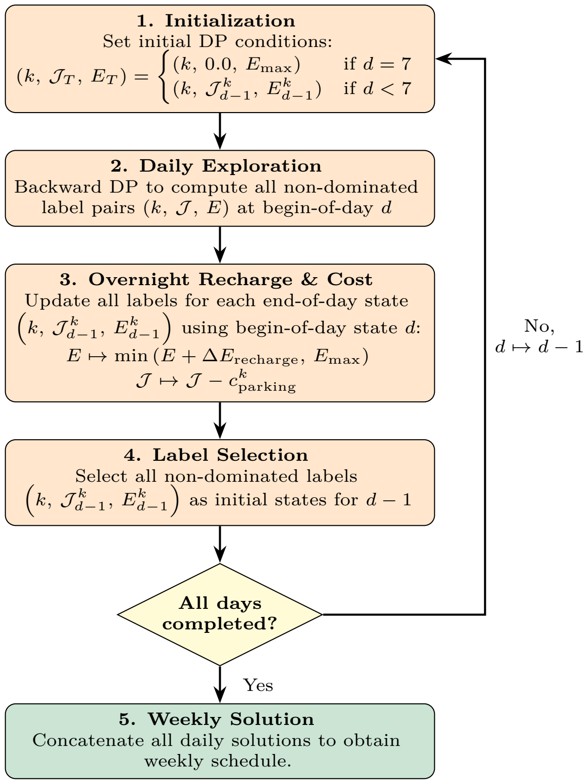


Figure 11 Five-step iterative flowchart of the *Weekly Schedule Constructor* for weekly flight schedule generation

III. Case Study & Verification

The FSEAR model is applied to a case study (CS) to evaluate its performance on realistic input data and to support model verification. The selected airline network is the *KLM Cityhopper* network, the regional subsidiary of *KLM Royal Dutch Airlines*, which primarily operates short-haul European routes from Amsterdam Schiphol Airport (AMS) using a fleet of Embraer aircraft. The current *KLM Cityhopper* fleet includes the conventional *Embraer* models: *E195-E2*, *ERJ-175*, and *ERJ-190* [44].

Network operations are reconstructed from a seven-day forecast obtained via *FlightRadar24* [1], including all departures from and arrivals to Amsterdam Schiphol (AMS). The Cityhopper sub-network is isolated by filtering the raw dataset based on aircraft type, using a conversion table compiled from multiple sources, such as the *International Civil Aviation Organization* (ICAO) Aircraft Type Designators registry [2] and KLM fleet

[1] `https://www.flightradar24.com/data/airlines/kl-klm/routes` [Accessed: 2025-04-08]
[2] `https://www.icao.int/publications/DOC8643/Pages/Search.aspx` [Accessed: 2025-04-15]

information[3].

The procedure for deriving the three case study sub-networks from the filtered Cityhopper network is described in Section III.A. Required airport-level data for the selected sub-networks are presented in Section III.B. This is followed by an overview of the conventional Embraer fleet and the conceptual all-electric and hybrid-electric aircraft considered in Section III.C. Finally, model verification based on the case study is provided in Section III.D.

A. Case Study Networks

Three distinct sub-networks, each limited to a maximum of ten airports, are constructed from the *KLM Cityhopper* network to explore varied operational scenarios. These are visualized as geographic maps of Europe in Appendix A.2, with corresponding weekly demand data detailed in Appendix A.3. Demand per origin-destination pair is estimated by multiplying the aircraft's seat capacity by an average load factor of 0.83 [44]. The three case studies are defined as follows:

1. *Case Study I: Closest Distance (CS-I)* Airports are selected based on their great-circle distance from AMS, emphasizing short-haul routes. This structure is particularly suitable for assessing electric or hybrid-electric aircraft performance under short-range, high-frequency operations.
2. *Case Study II: Highest Demand (CS-II)* Airports with the highest total weekly passenger totals are selected, focusing on commercially attractive routes. This variant aims at network optimization focused on revenue generation and seat utilization.
3. *Case Study III: Distance Demand (CS-III)* Airports are grouped into short-, medium-, and long-distance categories using quantile segmentation of their distance to AMS. Within each group, a fixed number of airports with the highest weekly demand (inbound and outbound) are selected, with the total number split evenly across categories. This case study enables performance comparison across varying ranges within a high-demand sub-network.

B. Airport Data

All airports in the *KLM Cityhopper* network are assessed based on the required input parameters. Geographical coordinates (longitude and latitude), IATA codes, and UTC offsets are retrieved from the open-source *Openflights* database[4], with the corresponding data provided in Appendix A.1 for reference. Each airport is categorized as a *Major Hub*, *Medium Regional*, or *Small Regional* based on 2024 annual passenger volumes from the *European Airport Traffic Statistics* (EATS) dataset by *Air Service One* [45]. This size classification determines airport-specific parking fees and recharging power levels, as detailed in Sections III.B.1 and III.B.2, respectively.

1. Day and Overnight Parking Cost

Parking fees, reflecting typical ground handling costs, are modeled as two components: an hourly rate during active operational hours (06:00-22:00) and a flat overnight fee for aircraft parked between 22:00 and 06:00. Airport classifications and aircraft MTOM categories are used to estimate both types of parking costs, as summarized in Table 3. The cost ranges are based on available pricing documents from European airports including AMS [46], CDG [47], BRU [48], LHR [49], HAM [50], ABZ [51], CPH [52], and NWI [53]. For implementation in this case study, the median value of each specified range is adopted as the representative day and parking overnight fee.

2. Airport Charging Power

Each airport is assigned a representative maximum charging power, determined by its size classification. The corresponding values are provided in Table 3. These estimates are based on an assumed 1.35 C-rate for the *Elysian E9X* [54, 55], combined with insights from recent advancements in charging technology reported by *Liang et al.* [4]. Due to limited publicly available data on charging infrastructure in the aviation sector, the assigned charging power values should be interpreted as approximate estimates.

[3] `https://www.klm.it/en/information/travel-class-extra-options/aircraft-types` [Accessed: 2025-04-15]
[4] `https://raw.githubusercontent.com/jpatokal/openflights/master/data/airports.dat`

Table 3 Overview of aircraft parking cost and charging power by airport category

Airport Category	MTOM Category	Parking (€/h)	Overnight (€)	Charging Power (MW)
Major Hub	Up to 10,000 kg	30 – 50	100 – 200	3
	10,001 – 50,000 kg	50 – 90	200 – 400	
	50,001 – 100,000 kg	90 – 130	300 – 500	
	Above 100,000 kg	130 – 180	400 – 600	
Medium Regional	Up to 10,000 kg	20 – 30	80 – 120	2
	10,001 – 50,000 kg	30 – 60	120 – 200	
	50,001 – 100,000 kg	60 – 90	200 – 350	
	Above 100,000 kg	90 – 120	300 – 450	
Small Regional	Up to 10,000 kg	10 – 20	50 – 100	1
	10,001 – 50,000 kg	20 – 40	100 – 200	
	50,001 – 100,000 kg	40 – 60	150 – 250	
	Above 100,000 kg	60 – 80	200 – 300	

C. Aircraft Database

The case study evaluates a mixed fleet comprising conventional, all-electric, and hybrid-electric aircraft to examine the influence of propulsion type on fleet composition within the *KLM Cityhopper* network.

The conventional reference fleet includes the in-service *Embraer E195-E2*, *ERJ-175*, and *ERJ-190* models, as introduced earlier in this section. For the all-electric category, the conceptual 90-seat *Elysian E9X* is considered, considered under three battery energy densities, 240, 360, and 440 Wh/kg, based on the design studies of *Wolleswinkel et al.* [54, 55]. These configurations provide a reference for zero-emission, medium-range electric performance. The hybrid-electric subset consists of four configurations: three 5%-hybridized aircraft (*ATR 72-600*, *Bombardier CRJ 200*, and *Bombardier CRJ 1000*) based on *Antunes* [13], and a 20%-hybridized conceptual parallel hybrid aircraft obtained from *Bonnin & Hoogreef* [56].

The full database includes three conventional aircraft, three all-electric *E9X* configurations (varying in battery energy density), and four hybrid-electric concepts. A technical summary of all aircraft used is presented in Table A.5, limited to parameters required by the FSEAR model. Fuel and electric ranges are linearized according to each aircraft's design range and degree of hybridization. Values or rows marked with an asterisk (*) denote computed or assumed entries. Details of the calculation methods used to compute these assumed values are provided in Appendix A.4.

Table 4 Detailed overview of available aircraft used in the case study, including key parameters

Parameter	**Unit**	ERJ 175	ERJ 190	E195 E2	E9X (240)	E9X (360)	E9X (440)	ATR 72-600	CRJ 200	CRJ 1000	Parallel (20%)
Aircraft Type[1]	[~]	CA	CA	CA	AEA	AEA	AEA	HEA	HEA	HEA	HEA
Seats	[~]	78	100	132	90	90	90	72	50	100	70
Speed	[km/h]	850	850	876	720	720	720	142	140	140	128
Design Range	[km]	3,334	3,890	4,315	500	800	1,000	1,370	3,148	3,056	926
Fuel Range	[km]	3,334	3,890	4,315	–	–	–	1,300	3,000	2,900	740
Electricity Range	[km]	–	–	–	500	800	1,000	70	148	156	186
MTOM	[kg]	40,370	51,800	62,500	76,000	76,000	76,000	28,690	28,098	51,985	46,900
Payload Mass	[kg]	10,094	13,047	16,150	9,120	9,120	9,120	7,920	5,500	11,000	7,500
Battery Energy*	[kWh]	–	–	–	8,400	13,000	15,000	390	840	1,500	6,700
Fuel Capacity	[L]	11,625	16,153	17,060	–	–	–	6,764	8,296	20,653	11,831
Recharging Power*	[kW]	–	–	–	11,000	18,000	20,000	1,100	1,100	2,000	9,000
Climb Time	[min]	18	16	16	16*	16*	16*	16*	16*	16*	17.5
Average TAT*	[min]	45	45	45	45	45	45	45	45	45	45
Acquisition Price	[M€]	24.0	29.0	34.0	34.8*	34.8*	34.8*	28.8*	26.8*	27.7*	30.0*
Source		[57, 58]	[59, 60]	[61, 62]	[54, 55]	[54, 55]	[54, 55]	[13]	[13]	[13]	[56]

[1] Aircraft type options: Conventional (CA), All-electric (AEA) and Hybrid-electric (HEA)
* Assumed or calculated value

D. Verification

This section outlines the verification of the FSEAR model using the case study introduced earlier. Verification ensures correct input processing, intermediate calculations, and expected outputs. In addition to unit tests on individual components, such as input parsing, output generation, and class behavior, the complete system is tested using representative case study data to validate key functionalities.

Verification is performed for both daily and weekly configurations. The daily setup serves to validate the core functionality of the *Path Explorer*, while the weekly setup ensures the correct behavior of the multi-day iterative scheduling process. Results from the daily and weekly verifications are presented in Section III.D.1 and Section III.D.2, respectively.

1. Daily Verification

The *Path Explorer* is verified using a single iteration in a daily configuration. This step ensures that the computed suboptimal path adheres to the theoretical methodology and internal logic of the model. Four key aspects are assessed to validate internal consistency and correctness: time-space alignment, energy flow integrity, emission attribution accuracy, and consistency of the objective function and demand. The verification is performed on the CS-I network using a daily configuration with ten hybrid-electric *Bombardier CRJ1000* aircraft and a 10-minute time interval. This configuration also incorporates a standard emission tax to penalize CO_2 emissions and account for environmental impact within the optimization. Results of this verification are shown inTable 5 and discussed below.

1. *Time-Space Alignment:* Confirms that each path maintains logical continuity in both time and space. As shown in Table 5, all ground arcs (GRD) preserve identical departure (N_i) and arrival (N_j) airports, ensuring spatial coherence. Flight arcs (FL) respect temporal feasibility such that the elapsed time between T_i and T_j does not exceed the sum of flight duration (T_{FL}) and the turnaround time (TAT) of 45 minutes. Any additional time is recorded as spare time.
2. *Energy Flow Integrity:* Ensures consistent application of energy consumption (E_{cons}) and recharging (E_{rec}) across both ground and flight arcs. As shown in Table 5, ground arcs contribute solely to battery recharging, while flight arcs involve energy depletion based on distance and aircraft type. The backward recursion confirms this behavior by checking that recharged energy is added to, and consumed energy subtracted from, the energy balance (E_{new}), aligning with the energy level at the preceding node (E_{old}). All flight segments comply with the recharging constraint in Equation (8), as described in Section II.E.2.
3. *Emission Attribution Accuracy:* Verifies that the reported electricity- and fuel-based emission values (e_{elec}, e_{fuel}) align with the energy consumption characteristics of the *Bombardier CRJ1000.* Emissions are attributed linearly based on the fractional use of battery and fuel energy, ensuring that any remaining flight distance beyond the battery range is covered by fuel, consistent with the hybrid-electric operation framework adopted in this study. The electricity and fuel emission values are validated using emission factors of $0.03\,\text{kg}\,\text{CO}_2/\text{kWh}$ and $3.15\,\text{kg}\,\text{CO}_2/\text{kg, fuel}$, respectively, as defined in Section II.A.1. The total emission (e_{tot}) is confirmed to equal the sum of electricity- and fuel-based emissions.
4. *Objective and Demand Consistency:* Validates that the objective values of individual arcs ($\mathcal{J}_{\text{arc}}$) and the cumulative objective ($\mathcal{J}_{\text{cumul}}$) scale linearly, with offsets reflecting fixed operational costs. These values reflect the distance-based fare structure and the served demand (D_s) per flight. Ground arc objective values accurately represent the parking fee of €120 per hour, applied uniformly across airport categories. Lastly, the total transported demand on the AMS-DUS OD pair has been verified not to exceed the 405-passenger limit in either direction.

In addition to the above verification aspects, the results highlight a key feature of the model that aligns with the underlying methodology. As illustrated in Table 5, the optimized daily schedule strategically conserves battery energy during flights corresponding to steps 4 and 9, where only a small fraction of battery energy is used alongside a greater share of fuel energy. These flights exhibit notably higher emissions compared to others. This behavior is explained by the preceding flight segments, which involve short ground times and limited recharging opportunities following energy-intensive flights. The model thus prioritizes battery conservation in anticipation of future operations, reflecting the model's logic to optimize overall long-term profitability.

Table 5 Suboptimal path of the *Bombardier CRJ1000* across ten airports in the CS-I network using a 10-minute time interval

#	T_i	N_i	d (km)	T_{FL}	TZ (~)	T_j	N_j	Action	$\mathcal{J}_{\mathrm{cumul}}$ (€)	$\mathcal{J}_{\mathrm{arc}}$ (€)	D_s (~)	E_{old} (~)	E_{cons} (~)	E_{rec} (~)	E_{new} (~)	e_{elec} (kg)	e_{fuel} (kg)	e_{tot} (kg)
1	06:00	AMS	-	-	-	07:00	AMS	GRD	27,200	-120	-	1.00	-	0.70	0.30	-	-	-
2	07:00	AMS	178	01:31	0	09:20	DUS	FL	27,300	5,840	100	0.30	0.70	0.21	0.79	31.5	1,250	1,280
3	09:20	DUS	-	-	-	09:30	DUS	GRD	21,500	-20.0	-	0.79	-	0.19	0.60	-	-	-
4	09:30	DUS	178	01:31	0	11:50	AMS	FL	21,500	5,670	100	0.60	0.40	0.60	0.40	18.0	2,100	2,110
5	11:50	AMS	178	01:31	0	14:10	DUS	FL	15,800	3,740	74	0.40	0.60	0.36	0.64	27.0	1,530	1,560
6	14:10	DUS	-	-	-	14:30	DUS	GRD	12,100	-40.0	-	0.64	-	0.34	0.30	-	-	-
7	14:30	DUS	178	01:31	0	16:50	AMS	FL	12,100	2,930	63	0.30	0.70	0.21	0.79	31.5	1,250	1,280
8	16:50	AMS	-	-	-	17:00	AMS	GRD	9,220	-20.0	-	0.79	-	0.19	0.60	-	-	-
9	17:00	AMS	178	01:31	0	19:20	DUS	FL	9,240	3,380	71	0.60	0.40	0.54	0.46	18.0	2,100	2,110
10	19:20	DUS	-	-	-	19:40	DUS	GRD	5,860	-40.0	-	0.46	-	0.26	0.20	-	-	-
11	19:40	DUS	178	01:31	0	22:00	AMS	FL	5,900	5,900	100	0.20	0.80	0.00	1.00	36.0	968	1,000

2. Weekly Verification

Following the verification of the *Path Explorer*, the model is further validated under a weekly configuration using the same network and settings, differing only in that a full weekly schedule is constructed and an unconstrained number of iterations is allowed. The simulation incorporates two comparable hybrid-electric aircraft types, the *Bombardier CRJ200* and *Bombardier CRJ1000*, to confirm that the model captures performance differences between aircraft across iterations.

In addition to verifying daily path construction within the weekly schedule, this verification focuses on iteration behavior. It assesses three critical properties: monotonic profit decrease, demand-removal consistency, and aircraft-type prioritization. These checks confirm that key mechanisms, such as profit prioritization and demand tracking, operate as intended over multiple iterations. A summary of results at the iteration level is presented in Table 6, with the corresponding analyses discussed below.

1. *Monotonic Profit Decrease:* Ensures that the model adheres to the expected declining profit across successive iterations. As demand is removed once served, subsequent iterations operate on a reduced network with lower remaining revenue potential, making higher profits unattainable. Consequently, the objective value should decrease monotonically. Table 6 confirms this behavior, demonstrating a consistent profit decline across iterations. A corresponding decline in total served demand per flight and flight frequency (# FL) is also observed, reinforcing the expected downward trend. Although these patterns are not strictly monotonic, they align with the model's methodology, which does not require strict monotonicity but supports an overall decreasing behavior across iterations.
2. *Demand-Removal Consistency:* Verifies that demand is correctly removed between iterations following the selection of the weekly path for the best-performing aircraft. As shown in Table 6, demand is removed cleanly with no residual reallocation in subsequent iterations. The table also confirms that once no profitable paths remain for the residual demand (D_{rem}), the model ends further iterations, thereby satisfying the FSEAR model's termination condition.
3. *Aircraft-Type Prioritization:* Verifies that the model appropriately selects different aircraft types across iterations based on changing network conditions and remaining demand. In Table 6, iteration 14 shows a shift to the *Bombardier CRJ200*, whereas previous iterations used the *Bombardier CRJ1000.* This transition aligns with model expectations as the smaller *CRJ200* offers lower per-passenger operating costs, making it more suitable as demand diminishes. This demonstrates that the aircraft assignment logic adapts appropriately to evolving operational conditions.

Table 6 Overview of the weekly routing schedule for *Bombardier CRJ1000* and *CRJ200* across ten airports in the CS-I network using a 10-minute time interval

Iter.	Status	Aircraft	N_{bow} [1]	N_{eow} [2]	$\mathcal{J}_{cumul}$ (€)	# FL (~)	$T_{FL,tot}$	D_s (~)	D_{rem} (~)	e_{elec} (kg)	e_{fuel} (kg)	e_{tot} (kg)
1	OK	B CRJ1000	AMS	LCY	173,000	38	72:09	3,617	46,508	1,060	92,800	93,800
2	OK	B CRJ1000	AMS	FRA	139,000	31	78:48	2,866	43,642	837	128,000	129,000
3	OK	B CRJ1000	DUS	AMS	126,000	33	76:13	2,805	40,837	909	116,000	117,000
4	OK	B CRJ1000	LCY	DUS	109,000	29	72:26	2,475	38,362	891	110,000	111,000
5	OK	B CRJ1000	FRA	AMS	91,900	27	71:36	2,209	36,153	904	108,000	109,000
6	OK	B CRJ1000	AMS	AMS	58,400	22	66:24	1,683	34,470	770	106,000	107,000
7	OK	B CRJ1000	AMS	AMS	43,100	18	71:57	1,398	33,072	702	127,000	128,000
8	OK	B CRJ1000	BLQ	AAL	37,400	15	70:52	1,232	31,840	594	133,000	134,000
9	OK	B CRJ1000	SVG	AMS	35,000	15	60:51	1,225	30,615	594	108,000	108,000
10	OK	B CRJ1000	AMS	GDN	25,900	12	63:48	1,028	29,587	468	125,000	125,000
11	OK	B CRJ1000	AMS	AMS	22,600	11	54:21	967	28,620	396	106,000	106,000
12	OK	B CRJ1000	AAL	BLQ	22,200	11	61:51	972	27,648	450	122,000	122,000
13	OK	B CRJ1000	AMS	SVG	6,850	9	45:42	750	26,898	405	84,700	85,100
14	OK	B CRJ200	GDN	GDN	4,430	16	81:41	730	26,168	285	64,700	65,000
15	$\mathcal{J}_{cumul} < 0$	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

[1] Begin of week departure airport
[2] End of week arrival airport

IV. Results & Discussion

This section presents the results of applying the FSEAR model to the *KLM Cityhopper* case study introduced in Section III, with the primary objective of evaluating the effect of partial versus full recharging strategies for electrified aircraft. The model is applied to three sub-networks, to enable consistent comparison across varying network structures. FSEAR generates weekly schedules under two energy configurations: *Full Recharging*, which permits flights only when the battery is fully charged, and *Partial Recharging*, which allows flights as long as sufficient energy is available. Each case study is simulated under both configurations, producing a structured set of comparative outputs. All model input parameters are detailed in Appendix B.

Section IV.A presents results for two mixed fleet configurations: one including conventional, all-electric, and hybrid-electric aircraft, and one limited to all-electric and hybrid-electric types. The configuration with conventional aircraft serves as a baseline to evaluate whether partial recharging encourages a shift away from conventional operations. However, the primary focus lies on the interaction between all-electric and hybrid-electric aircraft, allowing a clearer interpretation of partial recharging effects on electrified fleets. In contrast, Section IV.B examines the performance of homogeneous fleets composed exclusively of either all-electric or hybrid-electric aircraft. This section compares full and partial recharging configurations across both categories to assess performance differences. Additionally, a set of sensitivity analyses is conducted to evaluate how varying model parameters influence key outcomes such as financial profit, CO_2 emissions, and fleet composition, as described in Section IV.C.

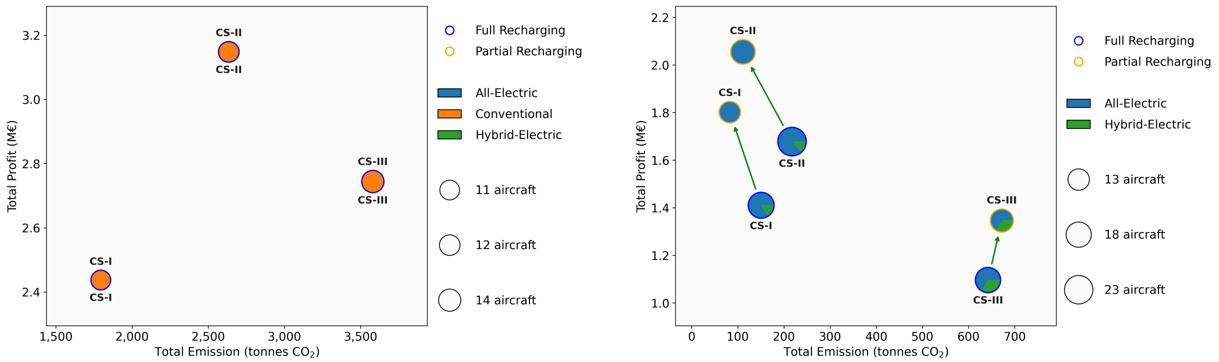
A. Comparative Analysis Using a Mixed Fleet Configuration

The impact of partial recharging on weekly financial profit and total CO_2 emissions (in tonnes) is evaluated across both mixed fleet configurations. Figure 12 presents the absolute fleet size and composition, as well as the resulting profit and CO_2 emissions under both the *Full Recharging* and *Partial Recharging* configurations for each of the three case studies. Relative changes resulting from partial recharging are summarized in Table 7, while Table 8 presents the relative differences between configurations that include conventional aircraft and those limited to all-electric and hybrid-electric fleets.

In the configuration including all aircraft types, Figure 12a shows that conventional aircraft dominate the fleet selection. This outcome indicates that, even with partial recharging, electrified aircraft do not yet offer a more financially attractive alternative under the current operational assumptions. The associated increase in CO_2 emissions is disproportionately large, highlighting the environmental trade-off of this configuration. A detailed comparison between configurations with and without conventional aircraft is provided in

Section IV.A.1.

Each case study is evaluated based on the configuration that excludes conventional aircraft, allowing clearer isolation and interpretation of the impact of partial recharging on electrified operations. Partial recharging results in substantial profit gains across all case studies, with improvements of approximately 25 %. In CS-I and CS-II, CO_2 emissions also decline due to a shift in fleet composition, where all-electric aircraft are favored over hybrid-electric types. As shown in Table 7, partial recharging consistently pushes operational results toward the upper-left quadrant indicating higher profits and lower emissions. In CS-III, while profit increases, emissions and fleet composition remain largely unchanged due to the specific operational constraints of the network. Detailed analyses per case study are provided in Sections IV.A.2 to IV.A.4.



(a) Conventional, all-electric, and hybrid-electric fleet

(b) All-electric and hybrid-electric fleet

Figure 12 Comparison of network profit and CO_2 emissions between partial and full recharging constraints under two mixed fleet configurations

Table 7 Relative differences in profit and CO_2 emissions due to partial recharging, based on the all-electric and hybrid-electric mixed fleet configuration (Figure 12b), evaluated across all case studies

Case Study	Profit (Δ%)	Emissions (Δ%)
CS-I: Closest Distance	+27.8	−45.1
CS-II: Highest Demand	+22.5	−48.9
CS-III: Distance Demand	+22.8	+4.66

Table 8 Relative differences in profit and CO_2 emissions when conventional aircraft are included in the mixed fleet configuration (Figure 12a) compared to excluded (Figure 12b), evaluated across all case studies

Case Study	Profit (Δ%)	Emissions (Δ%)
CS-I: Closest Distance	+35.2	+2070
CS-II: Highest Demand	+53.2	+2270
CS-III: Distance Demand	+103	+432

1. Impact of Including Conventional Aircraft in Fleet

The inclusion of conventional aircraft exerts a dominant influence on fleet composition. Even under partial recharging configurations, electrified aircraft are not selected in place of conventional types. Across all three case studies, regardless of distance or operational characteristics, the inclusion of conventional aircraft yields higher profit, but at the cost of substantially increased emissions, as shown in Table 8. The total fleet size is also considerably smaller than when using an all-electric and hybrid-electric fleet.

Conventional aircraft are favored over all-electric and hybrid-electric alternatives due to their cost structure and operational advantages. Although per-kilometer operating costs are comparable after applying emission tax, the lease cost for all-electric and hybrid-electric aircraft is 20 % higher. Since lease costs represent the dominant share of total costs, including all-electric and hybrid-electric types results in a more expensive fleet. Additionally, conventional aircraft achieve higher flight frequencies across all case studies, enabling greater demand to be served. The increase in transported passengers boosts total revenue, while lease costs remain fixed. As a result, cost efficiency per passenger improves, leading to higher profit margins for conventional aircraft and making them the preferred option.

These findings underscore a persistent challenge for the aviation industry, as conventional aircraft remain more financially attractive than electrified alternatives under current economic conditions and operational constraints. However, this financial advantage comes at a substantial environmental cost, with conventional fleets producing significantly higher CO_2 emissions. While partial recharging enhances electrified operations through greater flexibility and utilization, it remains insufficient in evaluated scenarios to overcome the profitability advantage of conventional aircraft.

2. Case Study I: Closest Distance

This case study focuses on short-range operations, where adopting partial recharging results in a complete shift in fleet composition. Under the *Full Recharging* configuration, the fleet includes sixteen all-electric *Elysian E9X* aircraft and three hybrid-electric aircraft, two *Bombardier CRJ200* and one *Bombardier CRJ1000*. In contrast, the *Partial Recharging* configuration operates with a smaller fleet of thirteen aircraft, all of which are all-electric *Elysian E9X* models.

This shift leads to a substantial reduction in total CO_2 emissions. Although electricity-related emissions increase by 21.9 %, this is more than offset by the complete elimination of fuel-based emissions, which were the dominant contributor under the full recharging setup. Additionally, flight frequency increases by 9.68 %, and transported demand rises by 7.97 %, resulting in a total profit gain of 27.8 %. Despite variation in flight frequency across the network, the set of served destinations remains unchanged due to the short-haul nature of this case study.

The results suggest that partial recharging can support fully electric, high-frequency operations on short-haul routes, offering a credible route toward low-emission regional aviation. This strengthens the case for sustainability-focused carriers like KLM Cityhopper, which aim to lead the transition to cleaner air transport [44].

3. Case Study II: Highest Demand

This case study targets high-demand routes and exhibits similar behavior to CS-I in terms of fleet recomposition, profit increase, and emission reduction. The fleet is downsized by removing three all-electric *Elysian E9X* and three hybrid-electric *Bombardier CRJ200* aircraft, resulting in a total of 17 aircraft. A profit increase of 22.5 % is achieved, slightly lower than in CS-I, while the total absolute CO_2 emissions decrease more substantially. This is partly attributed to CS-II's higher baseline profit and emissions levels.

Increases in flight frequency and transported demand are slightly smaller compared to CS-I, which can be attributed to longer average OD pairs distances. Route-level analysis indicates enhanced operational efficiency. For instance, on the AMS-BRE route, the number of flights decreases while transported demand is only halved, indicating better aircraft utilization. Most gains in flight frequency and transported demand occur on short- to mid-range routes, highlighting the stronger performance of partial recharging on these segments. Specifically, routes between 283 km and 367 km exhibit weighted average increases of 12.9 % in frequency and 11.3 % in demand. In contrast, longer routes exceeding 511 km exhibit slight declines, with weighted average reductions of 1.42 % in flight frequency and 0.890 % in transported demand. Similar trends of efficiency-driven reallocation are observed across other connections.

Overall, the results illustrate that partial recharging enhances profitability and lowers emissions on high-demand networks, particularly by improving efficiency on short- to mid-range routes.

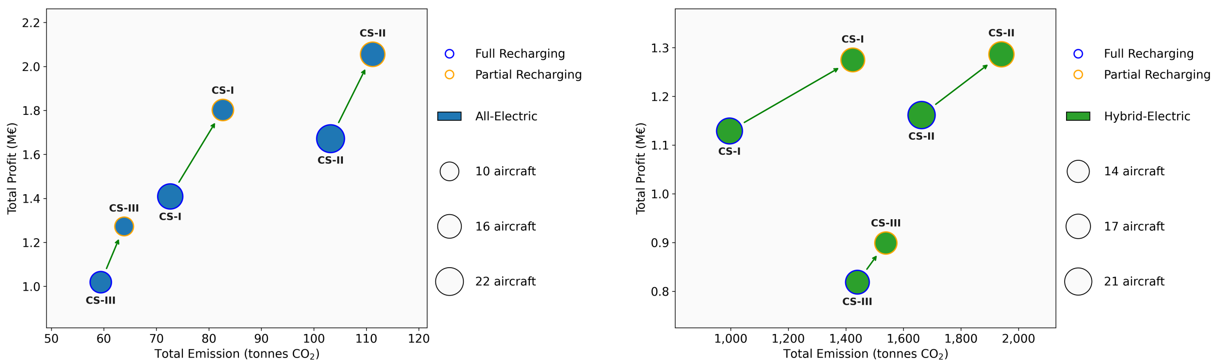
4. Case Study III: Distance Demand

The final case study evaluates a network comprising short-, medium- and long-haul regional routes, with OD pairs selected based on high demand, as introduced in Section III. While this configuration yields higher profits, it comes at the cost of increased total CO_2 emissions. Although the fleet size is reduced under the *Partial Recharging* configuration, the all-electric to hybrid-electric ratio remains unchanged at 2:1. Unlike CS-I and CS-II, where emissions declined due to the removal of fuel-intensive hybrid-electric aircraft, only one *Bombardier CRJ200* is excluded in this case. The remaining fleet still includes five *Bombardier CRJ1000* aircraft, which continue to contribute substantially to fuel-based emissions. Total emissions increase by 4.66 %, driven by a 12.5 % rise in electricity-based emissions and a 3.87 % increase in fuel-based emissions. Despite the higher relative growth in electricity-related emissions, fuel remains the dominant contributor to total CO_2 output. In the *Full Recharging* configuration, fuel accounts for 90.9 % and electricity for 9.10 % of total emissions. Under *Partial Recharging*, these shares shift slightly to 90.2 % and 9.80 %, indicating a modest rise in the relative contribution of electricity, though fuel continues to dominate in absolute terms.

The increase in emissions is accompanied by a 6.01 % rise in total flight frequency and a 6.65 % increase in total distance flown, indicating a more active network with broader coverage under the *Partial Recharging* configuration. Crucially, the total emission increase of only 4.66 % remains well below the growth in distance traveled, indicating a relative improvement in emission efficiency. When normalized per kilometer, this translates to approximately 1.87 % fewer CO_2 emissions per kilometer flown compared to the *Full Recharging* configuration. For instance, routes like AMS-SVG and AMS-FRA show substantial increases in frequency up to 24 % with modest emission contributions relative to distance covered and demand served. This highlights that the increase in absolute emissions is partly a trade-off for greater network productivity and accessibility, rather than a sign of inefficiency.

These results underline that while partial recharging may not always reduce total emissions, it enables a more flexible and productive network operation with improved emissions per unit of output, aligning with the broader goals of sustainable regional aviation. This shows that partial recharging could help airlines improve efficiency and network reach while maintaining progress toward sustainability, even when full electrification is not yet feasible.

B. Comparative Analysis using Homogeneous Fleet Configurations
The three case studies are evaluated under unconstrained homogeneous fleet configurations to isolate the performance of individual aircraft types. Restricting operations to either all-electric or hybrid-electric aircraft removes the influence of mixed-fleet interactions. The corresponding profit and emission outcomes are shown in Figures 13a and 13b. Detailed analyses for both fleet types are presented in Sections IV.B.1 and IV.B.2.



(a) All-electric fleet **(b)** Hybrid-electric fleet

Figure 13 Comparison of network profit and CO_2 emissions across case studies for unconstrained, homogeneous fleet configurations

1. All-Electric Fleet
The homogeneous all-electric fleet achieves substantial profit gains across all three case studies, ranging from 23.0 % to 27.9 %, alongside moderate emission increases of up to 13.8 %. These outcomes are consistent with the FSEAR model's assumption that electricity-based emissions scale linearly with distance flown. The profit increase corresponds with an average rise in flight frequency of approximately 10 %.

In CS-I, route-level analysis shows strong increases in flight frequency and transported demand, particularly at Humberside Airport (HUY) and Norwich International Airport (NWI), with frequency increases ranging from 33 % to 92 %, and transported demand increases from 29 % to 50 %. CS-II and CS-III show more stable patterns, with most route-level changes remaining within 20 %. Notably, CS-II reveals a redistribution of network activity under partial recharging, with fewer flights from Stuttgart Airport (STR) and more operations from Frankfurt Airport (FRA), despite unchanged transported demand at both locations.

Fleet-level analysis indicates that fewer aircraft are required under the *Partial Recharging* configuration. Those deployed also achieve higher utilization, particularly in early iterations. Profit per aircraft during the first five iterations is roughly twice that of the *Full Recharging* configuration, with similar gains in served demand.

The enhanced utilization and smaller fleet enabled by partial recharging significantly strengthen the operational feasibility of all-electric aircraft, which would otherwise remain constrained under full recharging.

2. Hybrid-Electric Fleet

The homogeneous hybrid-electric fleet exhibits a similar pattern to the all-electric configuration, with increases in both profit and total CO_2 emissions. However, unlike the all-electric case, where profit gains exceed emissions growth, the opposite holds true here. Partial recharging leads to modest profit increases ranging from 9.82 % to 12.9 %, while emissions rise more significantly, between 6.85 % and 43.0 %.

This pronounced increase in emissions is driven by a shift in the relative contributions of fuel and electricity. Across all case studies, fuel-based emissions increase while electricity-based emissions decline. This effect is most evident in CS-I, where fuel-related emissions rise by 44.3 % alongside a 30.3 % reduction in electricity emissions. Similarly, CO_2 per kilometer and CO_2 per Revenue Passenger Kilometer (RPK) also rise under partial recharging, ranging from 4.60 % to 36.3 %. These results highlight a key limitation of hybrid-electric configurations as partial recharging reduces total energy use through optimized consumption but simultaneously increases dependence on fuel. While it enables higher flight frequencies and profits, this benefit comes at the cost of increased fuel use and higher absolute CO_2 emissions.

Similar to the all-electric configuration, partial recharging improves operational efficiency in the hybrid-electric fleet, allowing a smaller fleet to perform more flights and serve greater demand. However, this comes at the cost of increased fuel dependence, raising concerns about long-term sustainability.

C. Sensitivity Analysis

The FSEAR model is subjected to a set of sensitivity analyses to assess how simulation outcomes respond to changes in key parameters and configurations. These analyses provide deeper insight into model behavior and help identify which factors most influence performance. All sensitivity tests are conducted across the full set of case studies to capture variability arising from differences in demand distribution and route lengths. Some case studies respond more strongly to certain parameter changes than others, ensuring a more representative and robust understanding of the model's overall behavior.

All sensitivity analyses are performed using a daily scheduling framework to improve computational efficiency, rather than the weekly schedule used in the main partial recharging configuration. Since the weekly schedule is constructed from daily simulations, this simplification has negligible impact on outcomes while reducing runtime by at least factor of seven. In some analyses, conventional aircraft are selectively included or excluded to better isolate the influence of specific variables.

A preliminary study is first conducted to determine an appropriate number of airports and the time discretization interval before analyzing core parameters. The results of this initial configuration study, which defines the fixed settings for the partial recharging analysis and all subsequent sensitivity analyses, are presented in Section IV.C.1. Subsequent sections explore the influence of charging profiles in Section IV.C.2, fuel and electricity prices in Section IV.C.3, and selected isolated single-parameter variations in Section IV.C.4.

1. Time Resolution and Network Size Analysis

Two key input parameters directly influence both the financial profit and computational runtime of the FSEAR model: the time resolution (defined by the interval between decision nodes) and the network size (determined by the number of included airports). Efficient execution of the partial recharging simulations and broader sensitivity studies depends on selecting suitable values for these parameters. The overall objective is to achieve a balance between computational tractability and minimal profit loss due to reduced model granularity.

The analysis uses a range of input values for the decision time interval (in minutes) and the number of airports in the network (including AMS), defined respectively as $\mathbf{T}_s$ = [10, 15, 20, 30, 60] and $\mathbf{N}_s$ = [6, 7, 8, 9, 10]. The resulting average performance across all case studies is shown in Figure 14, illustrating the relationship between these settings, model profitability, and computational runtime[5].

Figure 14 shows that increasing the number of airports has a significantly greater impact on financial profit than reducing the time interval between decision nodes. This is evident from the relative change compared to a selected baseline configuration ($\mathbf{T}_s = 60$, $\mathbf{N}_s = 6$), where expanding network size yields notably higher profit gains than improving time resolution. In terms of computational runtime, a diagonal trend emerges in which

[5]Simulations were executed on an Apple Macbook M1 Pro (10-core CPU and 16-core GPU) with 16 GB RAM.

runtime increases significantly, following an approximate 45° slope or steeper, toward the upper-left corner of the parameter space. This indicates that increased model granularity imposes steep computational costs. Particularly, shifts from 15 to 10 minutes or from 9 to 10 airports result in disproportionately high increases in runtime, signaling non-linear growth near the upper bounds.

Lastly, it is important to note that this analysis is based on a case study where demand exists only to and from AMS. This substantially reduces computational time, as the three-dimensional DP algorithm can exclude a large portion of the state space due to early dominance by zero-profit paths. Consequently, the curse of dimensionality is substantially mitigated in this scenario, though it may become more pronounced when modeling networks with OD demand between all airport pairs. Additionally, the included airport set is randomly selected. As different airport combinations can influence both computational speed and profit, this source of variability is not accounted for in the current analysis.

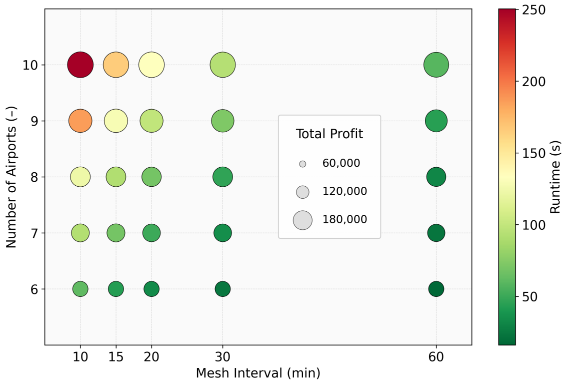


Figure 14 Impact of time resolution and network size on network profit and computational runtime (absolute values)

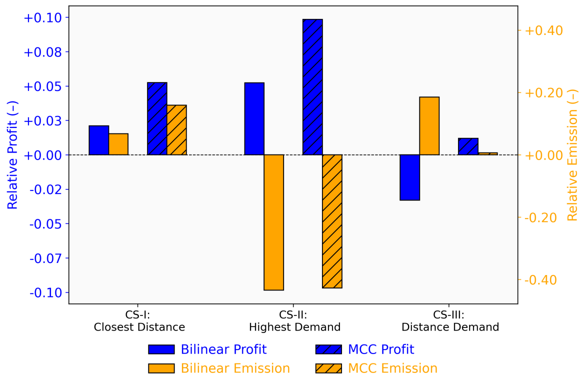


Figure 15 Impact of changing charging profile on network profit and CO_2 emissions, comparing bilinear and MCC profiles to linear charging as baseline

2. Charging Profile Analysis

The battery charging profile is a critical configuration parameter, especially under partial recharging, given its non-linear behavior and influence on profitability and emissions. This sensitivity analysis compares the baseline linear profile with two alternatives: a bilinear and a MCC profile [4] (see Appendix C for visualizations of the charging profiles). In the bilinear strategy, the first 80 % of the battery charges quickly, followed by a slower final 20 %, with total charging time equal to the linear profile. The MCC profile consists of five high-speed constant-current stages, leading to a 22.5 % increase in total charging speed. The analysis examines how these profiles affect profit and CO_2 emissions.

Figure 15 shows that both bilinear and MCC profiles improve profit in CS-I and CS-II. CS-I sees minor emission increases, while CS-II shows a substantial emission reduction. In CS-III, however, the bilinear profile leads to a slight profit decline despite improved charging efficiency, indicating more complex interactions between fleet composition and network constraints.

In CS-I, the fleet remains composed entirely of 9 *Elysian E9X* aircraft. Both bilinear and MCC profiles increase profit and emissions due to higher flight frequency, with MCC outperforming bilinear as a result of its faster recharge rate. In CS-II, emissions drop due to fleet shifts where the bilinear profile replaces a *Bombardier CRJ200* with an *Elysian E9X* and the MCC profile removes the CRJ200 entirely. This highlights MCC's advantage in reducing CO_2 emissions, primarily achieved through the removal of the fuel-based *Bombardier CRJ200*. CS-III shows limited sensitivity, as hybrid-electric aircraft remain necessary for long-range operations. The fleet composition does not change across profiles. Although the bilinear profile improves early iteration profits, total profit slightly declines due to suboptimal downstream route allocation, where early high-profit paths reduce residual demand for later iterations.

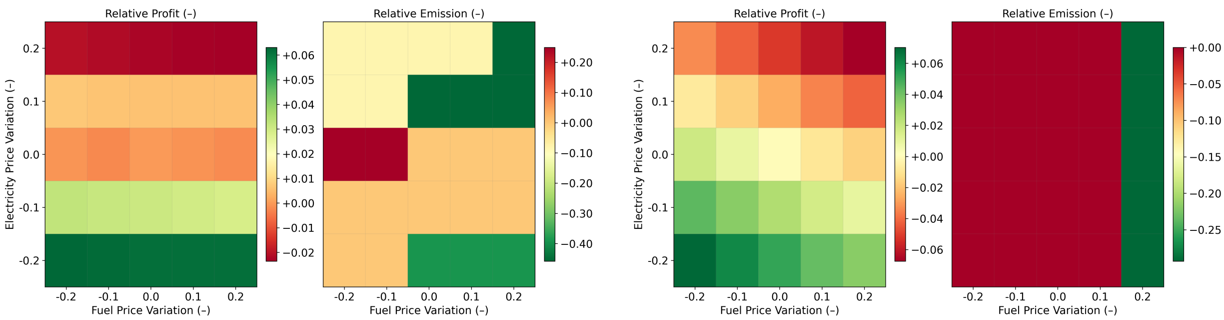
3. Energy Resource Price Analysis
Energy resource prices have a direct impact on both profitability and emissions, especially in all-electric and hybrid-electric fleet configurations, where the cost trade-off between electricity and fuel affects propulsion system selection. A two-dimensional sensitivity analysis is performed by scaling electricity and fuel prices using factor $f_{\text{res}} = [-0.2, -0.1, 0.0, 0.1, 0.2]$, relative to the baseline values of €0.1545 per kWh and €0.538 per liter, respectively. The results for CS-II and CS-III are shown as paired heatmaps of relative profit and CO_2 emissions in Figures 16a and 16b.

CS-I remains relatively stable in both profit and emissions due to the dominance of all-electric aircraft. Notable deviations arise primarily under reduced fuel price conditions. When fuel is scaled by $f_{\text{res}} = -0.2$, or by $f_{\text{res}} = -0.1$ in combination with a lower electricity price, one hybrid-electric *Bombardier CRJ200* is added to the fleet. This modification leads to a substantial rise in fuel-based CO_2 emissions, highlighting the fleet's sensitivity to relative energy price changes.

CS-II and CS-III exhibit contrasting sensitivities to energy price changes, as illustrated in Figures 16a and 16b. In CS-II, profit is primarily affected by electricity prices, following an approximately linear pattern, whereas changes in fuel prices have minimal impact. CS-III exhibits stronger and more symmetric sensitivity to both fuel and electricity prices. Its profit heatmap shows a diagonal gradient, where simultaneous increases in both prices reduce profitability, and joint decreases enhance it. This reflects CS-III's heightened sensitivity to the combined effects of electricity and fuel prices.

The differing sensitivities are primarily driven by variations in fleet composition across the two case studies. CS-II is predominantly operated by all-electric *Elysian E9X* aircraft, with no more than two hybrid-electric *Bombardier CRJ200* aircraft. In contrast, CS-III features a mixed fleet, typically consisting of five all-electric and three hybrid-electric aircraft in 80% of the evaluated configurations, making it more responsive to fuel price changes. This also affects emission outcomes. In CS-II, emissions increase when two hybrid-electric aircraft are added under scenarios with stable electricity and lowered fuel prices, reintroducing fuel-intensive operations. In CS-III, emissions decrease when a single *Bombardier CRJ1000* is removed from the fleet as a result of a fuel price increase to $f_{\text{res}} = 0.2$.

Overall, this analysis demonstrates how energy price variation influences profitability and emissions through fleet composition, with CS-III exhibiting the highest sensitivity, stemming from its dependence on both fuel- and electricity-based propulsion.



(a) CS-II: Highest Demand

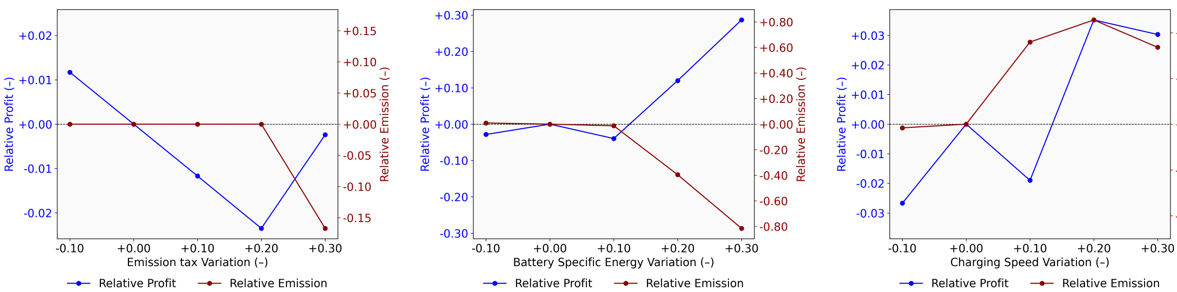
(b) CS-III: Distance Demand

Figure 16 Impact of varying resource prices on network profit and CO_2 emissions for CS-II: Highest Demand (a) and CS-III: Distance Demand (b)

4. Single Input Parameter Sensitivity Analyses
Following the preceding multi-dimensional and charging profile analyses, this part of the sensitivity study examines the model's response to isolated variations in individual parameters. Varying one parameter at a time enables direct attribution of model responses to specific factors, facilitating clearer verification of expected behavior. Three key parameters are examined: the emission tax, battery performance, and charging speed.

The emission tax is varied to assess its impact on fleet composition (including conventional aircraft) and total emissions, simulating the effect of stricter CO_2 taxation and promoting a shift toward lower-emission routes and increased electric propulsion use. Battery performance is assessed by increasing the energy density. This results in proportional gains in both electric and total range, representing an optimistic scenario aligned with projected technological advancements. Charging speed is varied in the same manner to represent the impact of improved infrastructure. Each parameter is scaled using the same relative adjustment factor, defined as $f_s = [-0.1, 0.0, 0.1, 0.2, 0.3]$, relative to baseline values and applied across all case studies.

Figure 17 presents outputs from each analysis based on case study III, selected due to its most pronounced deviations from expected trends. Figure 17a shows the expected trends for all emission tax variations, except for the transition from a 20 % to 30 % increase, which unexpectedly yields a profit increase. A similar deviation occurs in Figures 15 and 17b for a 10 % increase in battery energy density and charging speed, respectively. In all three cases, these deviations stem from increased model sensitivity in later iterations, where early routing decisions constrain later flexibility. This pattern reflects the model's structural limitations, namely the greedy demand removal and the sequential, priority-based aircraft assignment discussed in Section II. Although profit deviations are limited, emission changes are more significant. These shifts are primarily driven by changes in fleet composition, specifically the addition or removal of conventional or hybrid-electric aircraft, which disproportionately affect total emissions



(a) Emission Tax

(b) Battery Performance

(c) Charging Speed

Figure 17 Impact of single-parameter variations on network profit and CO_2 emissions for CS-III: Distance Demand

V. Conclusion

This paper addresses the current research gap in integrating airline planning with partial recharging, climate optimization, and electrified aircraft design. By concentrating on airline planning, this study contributes to the multidisciplinary gap without delving into aircraft-level design. The primary objective was to gain deeper insights into the operational effects of partial recharging strategies for electrified aviation within regional networks. The study focused on evaluating their implications for airline network profitability and carbon emission reduction. The central aim was to answer the following research question: *What is the effect of incorporating partial recharging strategies into flight scheduling and aircraft routing on airline network profitability and carbon emission reduction?*

To answer this question, the Flight Scheduling and Electrified Aircraft Routing (FSEAR) model was developed with partial recharging as a core feature. The model uses a sequential, iterative decision-making process in which, at each iteration, the best-performing aircraft is selected based on suboptimal routes computed for all available types in an unconstrained fleet. This process continues until all demand is served or no further profitable assignments remain. Route construction incorporates partial recharging via a three-dimensional time-space-energy recursive dynamic programming algorithm, where energy balance is explicitly modeled as the third state variable to optimize energy usage across the network. A multi-label dominance strategy simultaneously tracks objective value and energy balance, supported by a sub-optimal but consistent demand allocation mechanism. The resulting output is a weekly, near-optimal flight schedule along with the corresponding fleet composition.

The model was applied to three case studies derived from the *KLM Cityhopper* network, based on a seven-day schedule forecast. These case studies focused on sub-networks characterized by short-range connectivity, high-demand routes, and varying distances with high demand. The model was first verified using these scenarios, after which a comprehensive partial recharging and sensitivity analysis was conducted across all three networks to evaluate performance under diverse operational conditions. The available fleet included both conventional aircraft currently operated by *KLM Cityhopper* and conceptual all-electric and hybrid-electric aircraft obtained from various academic and industry studies.

Integrating partial recharging into the FSEAR model significantly improved network performance for a mixed all-electric and hybrid-electric fleet, in line with expectations from the developed methodology. Across all case studies, profit increased substantially, ranging from 22.47 % to 27.75 %. In two cases, fleet recomposition fully replaced hybrid-electric aircraft with all-electric alternatives, resulting in CO_2 emission reductions of 45.10 % and 48.89 %. The third case study, involving longer flight distances, showed a moderate emission increase driven by higher hybrid-electric flight frequency, accompanied by a reduction in fleet size and a gain in profit. These results demonstrate the strong operational benefits of partial recharging, confirming its potential to boost profitability while reducing emissions in most scenarios. This confirms that the research question concerning the impact of partial recharging on network profitability and carbon emission reduction has been effectively addressed.

While conventional aircraft remain more profitable under current conditions, this comes with significantly higher emissions. The improvements enabled by partial recharging show that electrified operations can already deliver meaningful environmental and operational gains, offering a promising direction for more sustainable regional aviation. By incorporating partial recharging into the analysis, this study presents a more realistic and nuanced view of electrified aircraft performance. Earlier studies may have underestimated this performance due to more restrictive assumptions. This broader perspective can influence how electrified aviation is assessed in both academic research and industry planning.

There is considerable potential to improve the research by integrating a more advanced aircraft dynamics formulation. The current framework simplifies energy consumption and omits payload-range interactions, limiting realistic aircraft behavior. A refined version of the Breguet range equation that accounts for variable hybridization ratios as a function of battery state-of-charge would more accurately capture performance under partial recharging. This would enable realistic payload-range trade-offs and account for fuel weight effects on energy use. Incorporating these dynamics would offer deeper insight into energy consumption, operational flexibility, and the feasibility of electrified aviation.

Building on this, future work should bridge the current gap between aircraft design and operational performance. While design aspects were beyond this studys scope, integrating them with the enhanced dynamics module would enable co-optimization of design and planning. A promising redesign direction is to vary battery size and payload within fixed mass and volume limits, adapting range and capacity to route demands. This approach supports more realistic modeling of the payload-range trade-off and enables more accurate assessments of how electrified aircraft should be designed for profitable and sustainable operations.

In parallel, the optimization framework itself can be improved by addressing two key structural limitations: the greedy removal of unserved demand and the sequential assignment of aircraft without regard for future interactions. A dedicated strategy for selecting and removing demand within the dynamic programming model could reduce suboptimal outcomes. Likewise, replacing the current priority-based aircraft assignment with a method that considers interdependencies across iterations would improve the quality of resulting schedules and fleet compositions.

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Appendices

A. Case Study Information

1. Airport Data

Table A.1 Airport selection and corresponding details for the three case studies, derived from the *KLM Cityhopper* regional route network

(a) CS-I: Closest Distance

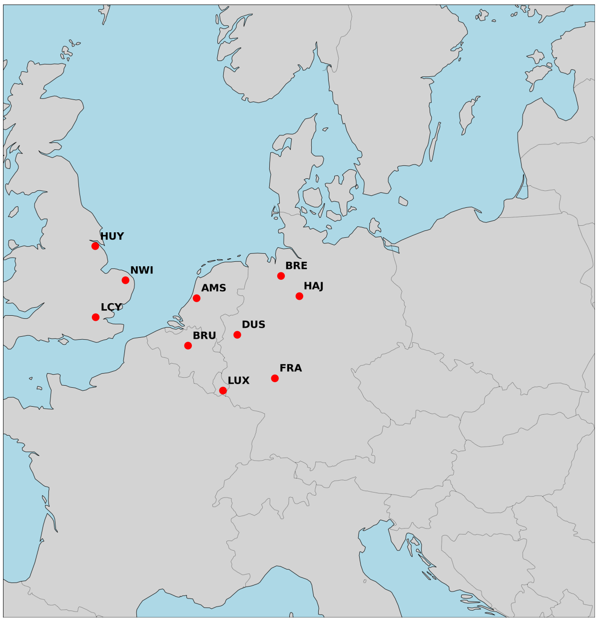
Code	Lat	Lon	Cat
AMS	52.3086	4.7639	L
BRE	53.0475	8.7867	M
BRU	50.9014	4.4844	L
DUS	51.2895	6.7668	L
FRA	50.0333	8.5706	L
HAJ	52.4611	9.6851	M
HUY	53.5744	-0.3508	S
LCY	51.5053	0.0553	M
LUX	49.6233	6.2044	M
NWI	52.6758	1.2828	S

(b) CS-II: Highest Demand

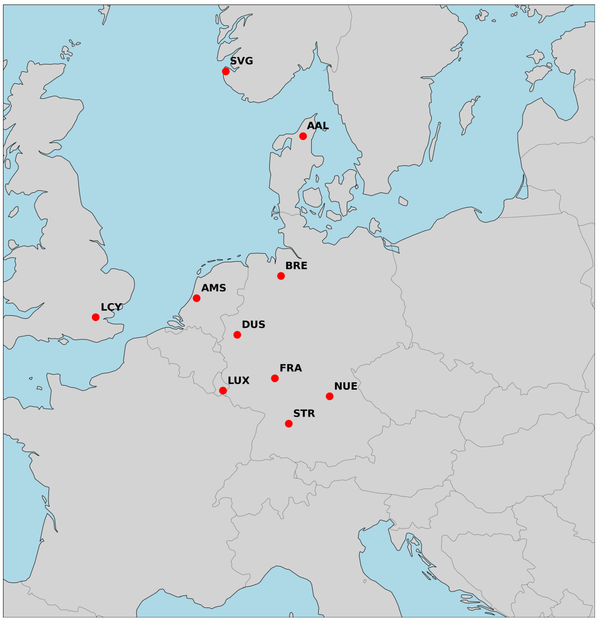
Code	Lat	Lon	Cat
AAL	57.0928	9.8492	M
AMS	52.3086	4.7639	L
BLQ	44.5354	11.2887	M
DUS	51.2895	6.7668	L
FLR	43.8100	11.2051	M
FRA	50.0333	8.5706	L
GDN	54.3776	18.4662	M
KRK	50.0777	19.7848	M
LCY	51.5053	0.0553	M
SVG	58.8767	5.6378	M

(c) CS-III: Distance Demand

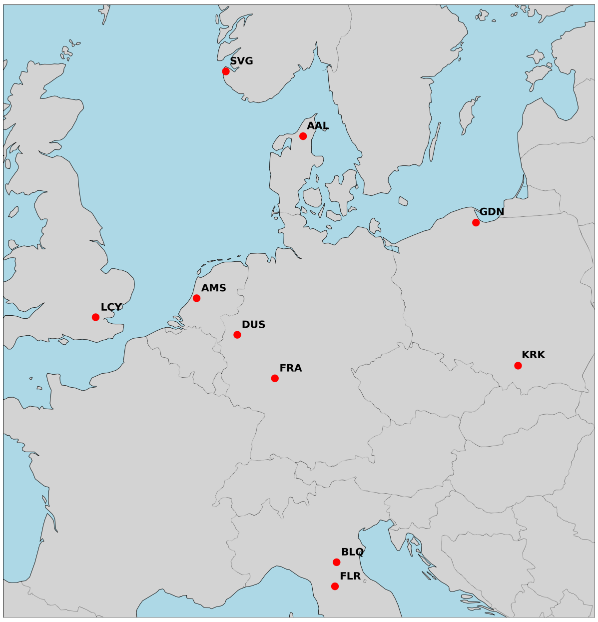
Code	Lat	Lon	Cat
AAL	57.0928	9.8492	M
AMS	52.3086	4.7639	L
BRE	53.0475	8.7867	M
DUS	51.2895	6.7668	L
FRA	50.0333	8.5706	L
LCY	51.5053	0.0553	M
LUX	49.6233	6.2044	M
NUE	49.4987	11.0781	M
STR	48.6899	9.2220	M
SVG	58.8767	5.6378	M



(a) CS-I: Closest Distance



(b) CS-II: Highest Demand



(c) CS-III: Distance Demand

Figure A.1 Geographic layout of the three case studies derived from the *KLM Cityhopper* regional route network

Table A.2 Weekday passenger demand to and from AMS with flight distances for selected airports in CS-I: Closest Distance

Airport	**Dist.** (km)	**Arrivals to AMS** Mon	Tue	Wed	Thu	Fri	Sat	Sun	**Departures from AMS** Mon	Tue	Wed	Thu	Fri	Sat	Sun
BRE	283	322	644	322	322	322	239	322	322	644	322	322	322	239	322
BRU	158	229	677	239	229	229	239	322	239	657	239	229	219	239	322
DUS	178	385	926	395	385	385	405	405	385	926	395	385	385	405	405
FRA	367	478	956	478	478	478	405	478	478	956	478	478	478	405	478
HAJ	334	302	604	302	302	302	229	312	302	604	302	302	302	229	312
HUY	370	249	498	0	249	249	249	249	249	415	0	249	249	249	249
LCY	335	664	1328	664	664	664	249	664	664	1328	664	664	581	249	498
LUX	315	395	780	395	395	405	239	302	395	780	395	405	405	239	302
NWI	239	302	604	219	302	156	229	146	302	604	219	302	156	229	146

Table A.3 Weekday passenger demand to and from AMS with flight distances for selected airports in CS-II: Highest Demand

Airport	**Dist.** (km)	**Arrivals to AMS** Mon	Tue	Wed	Thu	Fri	Sat	Sun	**Departures from AMS** Mon	Tue	Wed	Thu	Fri	Sat	Sun
AAL	624	312	644	322	312	312	312	322	312	644	322	312	312	312	322
BRE	455	322	644	322	322	322	239	322	322	644	322	322	322	239	322
DUS	676	385	926	395	385	385	405	405	385	926	395	385	385	405	405
FRA	789	478	956	478	478	478	405	478	478	956	478	478	478	405	478
LCY	887	664	1328	664	664	664	249	664	664	1328	664	664	581	249	498
LUX	865	395	780	395	395	405	239	302	395	780	395	405	405	239	302
NUE	848	322	644	322	322	322	322	322	322	644	322	322	322	322	322
STR	935	332	820	405	405	405	405	415	332	820	405	405	405	405	415
SVG	318	395	800	395	322	312	229	322	395	800	395	322	312	229	322

Table A.4 Weekday passenger demand to and from AMS with flight distances for selected airports in CS-III: Distance Demand

Airport	**Dist.** (km)	**Arrivals to AMS** Mon	Tue	Wed	Thu	Fri	Sat	Sun	**Departures from AMS** Mon	Tue	Wed	Thu	Fri	Sat	Sun
AAL	624	312	644	322	312	312	312	322	312	644	322	312	312	312	322
BLQ	1400	249	498	249	249	249	249	239	249	498	249	249	249	249	239
DUS	676	385	926	395	385	385	405	405	385	926	395	385	385	405	405
FLR	1480	166	770	166	166	166	166	166	166	770	166	166	166	166	166
FRA	789	478	956	478	478	478	405	478	478	956	478	478	478	405	478
GDN	618	312	624	302	312	312	249	312	312	624	302	312	312	249	312
KRK	1017	239	717	166	239	239	83	156	239	717	166	239	239	83	156
LCY	887	664	1328	664	664	664	249	664	664	1328	664	664	581	249	498
SVG	318	395	800	395	322	312	229	322	395	800	395	322	312	229	322

Table A.5 Overview of available aircraft in the case study with corresponding parameters

Parameter	**Unit**	ERJ 175[1]	ERJ 190[2]	E195 E2[3]	E9X (240)[4]	E9X (360)[5]	E9X (440)[6]	ATR 72-600[7]	CRJ 200[8]	CRJ 1000[9]	Parallel (20%)[10]
Aircraft Type†	[~]	CA	CA	CA	AEA	AEA	AEA	HEA	HEA	HEA	HEA
Seats	[~]	78	100	132	90	90	90	72	50	100	70
Speed	[km/h]	850	850	876	720	720	720	142	140	140	128
Design Range	[km]	3,334	3,890	4,315	500	800	1,000	1,370	3,148	3,056	926
Fuel Range	[km]	3,334	3,890	4,315	–	–	–	1,300	3,000	2,900	740
Electricity Range	[km]	–	–	–	500	800	1,000	70	148	156	186
MTOM	[kg]	40,370	51,800	62,500	76,000	76,000	76,000	28,690	28,098	51,985	46,900
Payload Mass	[kg]	10,094	13,047	16,150	9,120	9,120	9,120	7,920	5,500	11,000	7,500
Battery Energy*	[kWh]	–	–	–	8,400	13,000	15,000	390	840	1,500	6,700
Fuel Capacity	[L]	11,625	16,153	17,060	–	–	–	6,764	8,296	20,653	11,831
Recharging Power*	[kW]	–	–	–	11,000	18,000	20,000	1,100	1,100	2,000	9,000
Climb Time	[min]	18	16	16	16*	16*	16*	16*	16*	16*	17.5
Average TAT*	[min]	45	45	45	45	45	45	45	45	45	45
Acquisition Price	[M€]	24.0	29.0	34.0	34.8*	34.8*	34.8*	28.8*	26.8*	27.7*	30.0*
Source		[57, 58]	[59, 60]	[61, 62]	[54, 55]	[54, 55]	[54, 55]	[13]	[13]	[13]	[56]

† Aircraft type options: Conventional (CA), All-electric (AEA) and Hybrid-electric (HEA)
* Assumed or calculated value
[1] Embraer ERJ-175
[2] Embraer ERJ-190
[3] Embraer E195-E2
[4-6] Elysian E9X with 240, 360, 440 Wh kg $^{-1}$ (pack) batteries
[7] ATR 72-600
[8] Bombardier CRJ-200
[9] Bombardier CRJ-1000
[10] Conceptual Parallel hybrid

Battery Energy
Battery energy (E_{battery}) is derived from reported mass fractions where available. If not, it is calculated from battery mass (M_{battery}) and pack-level energy density (ϵ_{pack}), as shown in Equation (A.1).

$$E_{\text{battery}} = M_{\text{battery}}/\epsilon_{\text{pack}} \tag{A.1}$$

Recharging Power
Maximum recharging power ($P_{\text{recharging}}$) is based on a C-rate of 1.35, following assumptions in the conceptual Elysian E9X study by *Wolleswinkel et al.* [54, 55]. This value is applied across all-electric aircraft, as shown in Equation (A.2).

$$P_{\text{recharging}} = \text{C-rate} \cdot E_{\text{battery}} \tag{A.2}$$

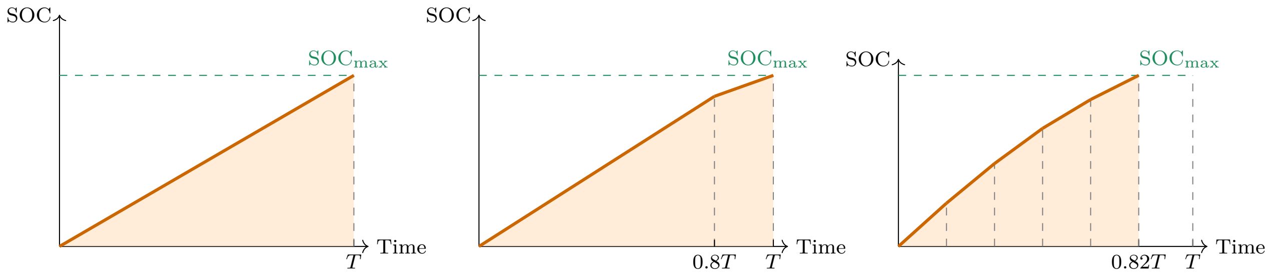
Average TAT and Climb Time
Turnaround time (TAT) is assumed equal for all aircraft, consistent with the methodology where TAT is decoupled from recharging behavior. Climb time is similarly standardized based on comparable climb performance among considered aircraft.

B. Model Input Parameters

Table B.6 Model input parameters used in the simulation framework

Category	**Parameter**	**Value**
Operational settings		
Start of day	`start_of_day`	06:00
End of day	`end_of_day`	22:00
LTO speed fraction	`lto_speed_fraction`	0.5
Pricing and cost factors		
Fuel price (€/l)	`fuel_price`	0.538
Electricity price (€/kWh)	`electricity_price`	0.1545
Carbon tax (€/ton CO_2)	`carbon_emission_tax_per_ton`	75
Lease cost factor	`lease_cost_factor`	0.0835
US$ to € conversion	`conversion_USD_to_EU`	0.91
Fare calculation		
Scaling coefficient a	`scaling_coefficient_a`	15
Elasticity exponent b	`elasticity_exponent_b`	-0.70
Fixed base fare c	`fixed_base_fare_c`	0.043
Crew cost and constraints		
Seats per cabin attendant	`seats_per_cabin_attendant`	50
Flight hours per captain	`hours_per_captain`	10
Crew overhead factor	`crew_overhead_factor`	0.26
Captain salary (USD)	`crew_salary_captain_USD`	97900
Copilot salary (USD)	`crew_salary_copilot_USD`	38000
Cabin crew salary (USD)	`crew_salary_cabin_attendant_USD`	21700
Annual flight hours	`crew_annual_flight_hours`	1000
Travel expense factor	`crew_travel_expense_factor`	7.0
Battery and energy parameters		
Recharging during TAT (TATF)	`recharging_during_TAT`	0.7
Energy consumption increment	`energy_increment`	0.1
Major hub charging power(kW)	`large_airport_recharging_power`	3000
Medium regional airport charging power (kW)	`medium_airport_recharging_power`	2000
Small regional airport charging power (kW)	`small_airport_recharging_power`	1000
Environmental constants		
Fuel density (kg/L)	`density_fuel`	0.803
CO_2 emission index fuel (kg/L)	`carbon_emission_index_fuel`	3.16
CO_2 emission index electricity (kg/kWh)	`carbon_emission_index_electricity`	0.03
Passenger and aircraft assumptions		
Passenger mass (kg)	`single_passenger_weight`	100

C. Charging Profile Visualization



(a) Linear   **(b)** Bilinear   **(c)** MCC (22.5% faster speed)

Figure C.2 Charging profiles for three charging strategies (normalized) with dashed lines showing phase transitions

2
Research Proposal

Research Proposal

Electrified aircraft planning with integrated partial recharging, climate optimization and aircraft design

Aerospace Engineering Thesis

Wessel Kruidenier

Delft University of Technology

TU Delft

Research Proposal

Electrified aircraft planning with integrated partial recharging, climate optimization and aircraft design

by

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Student number:	4834232	
Date:	Saturday 14th June, 2025	
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Cover: [1] (Modified)
Style: TU Delft Report Style, modified by W. L. Kruidenier

Summary

The aviation sector is experiencing a rapid annual growth, with air traffic expected to continue growing at a similar rate. This growing industry brings significant environmental concerns regarding greenhouse gases and other considerations. In response, international institutes have set worldwide climate targets to limit the temperature rise, as established by the *Paris Agreement* in 2015. In addition to these international climate goals, several aviation institutes have set their own targets, including the *NASA N+i* and *Fly The Green Deal* initiatives, to ensure that the aviation industry is able to meet the required climate impact reductions. As a result of these measures, the pressure on airlines and aircraft manufacturers has increased to adopt more innovative solutions. Electrified aviation, consisting of all-electric and hybrid-electric aircraft, provides a promising opportunity to achieve these targets. A key factor in realizing electrified aviation, as a replacement for conventional aviation, is the advanced integration of aircraft design and operational research.

The development of electrically driven aircraft has highlighted critical areas for its innovation: electrified aircraft design, aircraft performance and battery technology. The architectures of electrified aircraft, categorized by the degree of hybridization, directly impacts the performance within an airline network. Besides aircraft design considerations, performance optimization such as mission profile optimization and optimal in-flight energy distribution contributes to more efficient energy usage, directly effecting overall climate impact. Battery technology, as a vital driver for electrified aviation, directly influences fundamental aircraft design aspects and operational efficiency through recharging strategies. Alternative, more-efficient recharging strategies have been proposed to replace conventional CC-CV charging: boost charging and multi-stage charging.

In parallel, operational aspects of electrified aviation play a crucial role in driving an airline network's performance. The airline planning process, primarily flight scheduling and aircraft assignment, is a critical part of achieving improved operational efficiency. Over the past decades, multiple studies have enhanced the performance of conventional aircraft by applying optimization techniques such as mixed-integer linear programming and dynamic programming models to approach these problems. Various model variations have been developed, incorporating complex features such as passenger demand, spill cost and recapture, and time flexibility. In addition to this, many researchers have explored the benefits of integrating flight scheduling and aircraft routing, demonstrating improved operational efficiency and network performance.

Integrating these two key elements, aircraft design and performance with operational considerations, presents opportunities for enhanced overall performance. Earlier research has demonstrated promising effects when airline planning was coupled with either climate optimization or aircraft design. While some research has successfully integrated these three disciplines, adding partial recharging into the framework becomes a vital consideration for electrified aviation. This development leads to a fully integrated system that merges airline planning with partial recharging, climate optimization, and electrified aircraft design.

The reviewed literature highlights a research gap in the integration of airline planning with partial recharging, climate optimization and electrified aircraft design. Addressing this research gap, a research question and objective have been formulated to explore the impact of partial recharging strategies on airline network performance. The final research objective is defined as follows:

> *This research aims to analyze the impact of partial recharging strategies on airline network performance by optimizing the integration of flight scheduling and aircraft assignment with recharging strategies and electrified aircraft design, while maximizing profitability, reducing carbon emissions and adhering to electrified aircraft constraints.*

The approach to achieving this objective has been structured into five main phases. It begins with the development of a comprehensive methodology and computational model. Following this, a model verification process will ensure reliability and accuracy. Once verified, the model will be applied to a case study for both validation and comparative purposes. Finally, the last phase comprises the development of the article and the corresponding preparation of the research defense.

Contents

Nomenclature

Abbreviations

ACARE	Advisory Council for Aeronautics Research in Europe
ARP	Aircraft Routing Problem
BESS	Battery Electrical Storage System
BSFC	Brake-Specific Fuel Consumption
CAGR	Compounded Annual Growth Rate
CC	Constant-Current
CC-CV	Constant-Current Constant-Voltage
CV	Constant-Voltage
DDP	Deep Discharge Protection
DP	Dynamic Programming
EC	European Commission
EIS	Entry into Service
ERF	Effective Radiative Forcing
FAM	Fleet Assignment Model
FAP	Fleet Assignment Problem
GHG	Greenhouse Gases
HEP	Hybrid-Electric Propulsion
ICAO	International Civil Aviation Organization
IFAM	Itinerary-Based Fleet Assignment Model
ISD-FAM	Integrated Schedule Design and Fleet Assignment Model
LAB	Lithium-Air Batteries
LFP	Lithium-Iron-Phosphate
LIB	Lithium-Ion Battery
LMO	Lithium-Manganese-Oxide
LP	Linear Programming
LSB	Lithium-Sulfur Batteries
LTO	Landing and Take-Off cycle
LTO	Lithium-Titanate
MCC	Multistage Constant Current
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non Linear Programming

MRP	Maintenance Routing Problem	
N.A.	Not Available	
NASA	National Aeronautics and Space Administration	
NCA	Lithium-Cobalt-Aluminum	
NMC	Lithium-Nickel-Manganese-Cobalt	
NOD	Number of Propulsive Devices	
PLIB	Post-Lithium-Ion Battery	
PMF	Passenger Mix Flow	
RF	Radiative Forcing	
ROC	Rate of Climb	
SD-FAM	Schedule Design and Fleet Assignment Model	
SoC	State of Charge	
SSB	Solid-State Batteries	
TAT	Turn-Around Time	
WSDOT	Washington State Department of Transportation	

Chemical Formulas

CO_2	Carbon Dioxide
SO_2	Sulfur Dioxide
NO_x	Nitrogen Oxide

Greek Symbols

η_1	Efficiency Factor for Propulsion	–
η_2	Efficiency Factor for Energy Conversion	–
η_3	Efficiency Factor for Overall System	–
η_{BtT}	Efficiency Chain, Battery-to-Thrust	–
Γ_{fuel}	Generator Throttle Setting	%
ρ	Air Density	kg/m^3

Roman Symbols

Φ	Supplied Power Ratio	%
$\mathrm{SOC}_{\mathrm{cont}}$	Contingency State of Charge	%
tf	Trapped Fuel Fraction	–
A_r	Rotor Area	m^2
C_P	Rotor Power Coefficient	–

E	Energy	J
E_b	Battery Energy	J
e_f	Specific Energy of Fuel	J/kg
$E_{0,\text{tot}}$	Total Initial Energy	J
$E_{\text{aero,drag}}$	Aerodynamic Drag Energy	J
E_{battery}	Battery Energy	J/kg
e_{bat}	Specific Energy of Battery	J/kg
E_{kinetic}	Kinetic Energy	J
E_{nc}	Energy (non-consumable resources)	J
$E_{\text{potential}}$	Potential Energy	J
E_{tot}	Total Energy Source	J
f_N	Value of an N-stage Process	–
g	Gravitational Acceleration	m/s^2
H_E	Hybridization of Energy Source	–
H_P	Hybridization of Power	–
L/D	Lift-to-Drag Ratio	–
m	Mass	kg
m_{battery}	Battery Mass	kg
$m_{\text{fuel,ice}}$	Fuel Mass of Internal Combustion Engine	kg
P	State Value	–
P_m	Motor Power	W
P_{ice}	Power of the Internal Combustion Engine	W
P_{tot}	Total Power	W
$P_{\text{w,max}}$	Maximum Power	W
R	Range	m
$R(S, P)$	Reward Value of Decision S for State P	–
R_{alt}	Alternate Airport Range	m
R_{max}	Maximum Range	m
R_{OC}	Operational Cruise Range	m
S	Decision Value	–
t	Time	s
t_{l}	Aircraft Loiter Time	s
v	Velocity	m/s
V_w	Wind Speed	m/s
v_{l}	Aircraft Loiter Speed	m/s
W_{Bat}	Battery Weight	kg
W_{OE}	Operating Empty Weight	kg

W_{PL}	Payload Weight	kg

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1 Introduction

The aviation industry has experienced a steady upward trend over the past few decades, with persisting expected annual growth rates of 4.4 % continuing in the coming years [2–4]. Despite a temporary drop in CO_2 emissions during the COVID-19 pandemic, current emissions have returned to pre-pandemic levels [3, 5]. As both *Boeing* and *Airbus* predict annual traffic growth in the next two decades, the aviation sector's contribution to global greenhouse gas emissions remains a concern [3, 4]. In response to global warming, various entities have established ambitious climate reduction goals. In 2015, the *Paris Agreement* was established to address the rising global temperature [6]. Similar to these international initiatives, aviation institutes have introduced sector-specific initiatives for emission reduction such as *NASA N+i* and *Fly The Green Deal* [7, 8].

The aviation industry must adopt innovative solutions to align with these targets [9]. Among these solutions, electric and hybrid-electric aircraft have emerged as an effective approach for mitigating these emissions [10–12]. In addition, aircraft electrification can provide significant advancements in the decarbonization of the aviation industry, as it is widely recognized that the required overall climate performance can only be achieved through alternative fuels and energy resources [5, 13, 14]. The integration of airline planning with other disciplines such as climate optimization and aircraft design can further enhance performance and reduce climate impact [15, 16]. Lastly, the integration of battery charging considerations in airline planning is considered a crucial step in making electrified aviation a viable alternative to conventional aviation [10]. Altogether, these considerations illustrate the need to explore the integration of electrified aircraft with aforementioned disciplines.

This literature study aims to provide an overview of current literature that contributes to the understanding of integrating multiple disciplines into airline planning. Additionally, this literature offers essential background information regarding aircraft electrification and operational research aspects of conventional airline planning. The research focuses on the integration of airline planning with climate optimization, recharging strategies, and aircraft design, as schematically represented in Figure 1.1. This proposal seeks to identify the research gap in the integration of disciplines from current literature. The identification of the research gap will serve as a basis for the formulation of the research questions and sub-questions, and the research objective. Altogether, these elements will form the foundation of the research proposal.

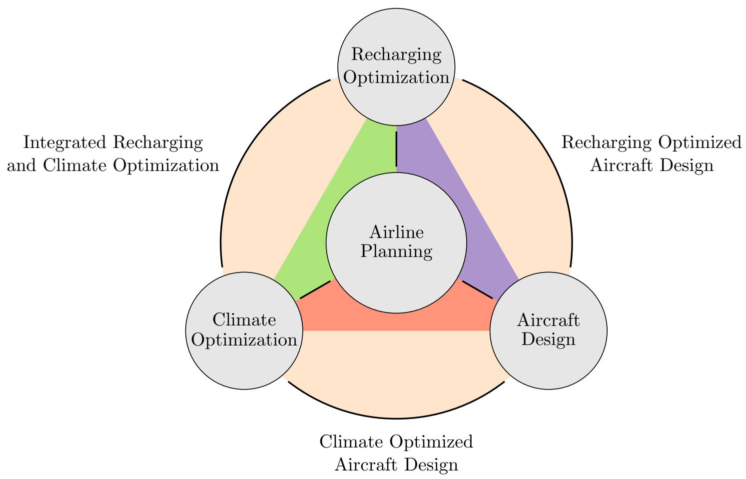


Figure 1.1: Schematic overview representing the integration of airline planning with related disciplines

This research proposal is structured to provide a comprehensive overview of the integration of electrified aviation with airline planning. General background information on recent developments in the aviation industry, focusing on growth and climate impact, is presented in chapter 2. Additionally, this chapter includes a brief overview of current climate goals established by major entities and highlights the challenge airline companies face in achieving these targets. Following this, chapter 3 outlines key aspects of aircraft electrification, focusing on aircraft design and performance, and battery and recharging technology. Consequently, chapter 4 dives into the operational research of the current airline planning process, outlining conventional planning processes, mathematical solving techniques and past studies on complex models. The integration of airline planning with disciplines, including climate optimization, recharging strategies, and aircraft design, are in more detail discussed in chapter 5. Furthermore, this chapter illustrates the integration of these disciplines through supported studies and provides an overview of the current state of research in this area. Chapter 6 summarizes the conclusion drawn from the reviewed literature, identifies the research gap, formulates the research question, sub-questions, and objective. This research proposal closes of with a research approach and preliminary planning schedule in chapter 7 and chapter 8, respectively.

2
Aviation Trends and Climate Goals

Over the past decades, the aviation industry has experienced an average annual growth of 4.4 % and is expected to continue to grow further in the future [2]. Although the recent COVID-19 pandemic temporarily reduced the global emission of CO_2 from 915 million metric ton in 2019 to 495 million metric ton in 2020, the current levels are back to pre-COVID levels, according to *Boeing* [3, 5]. The two largest aircraft producing companies, *Boeing* and *Airbus*, both expect in their forecast until 2043 a positive annual traffic growth of 4.7 % and 3.6 %[1] [3, 4]. It is expected that this still growing industry will result in an increasing negative impact on greenhouse gasses (GHG). For this reason, there is a critical need for the decarbonization of the aviation industry in order to contribute to worldwide advances of sustainability goals.

In 2015, the global treaty known as the *The Paris Agreement* was established, which aimed at reducing GHG emissions across all sectors [6]. This first major worldwide initiative strives to ensure that global temperatures do not exceed 2 °C above pre-industrial levels. According to the *European Commission* (EC), the aviation sector contributes approximately 2 % to the total global CO_2 emissions in 2022 and is growing faster than other modes of transportation [17]. The contribution of the aviation industry in Europe is even higher, namely in the range of 3.8 % - 4 % (2022) [17]. Furthermore, the International Civil Aviation Organization (ICAO) have predicted that the international aviation GHG emissions could increase up to three times the emissions values of those in 2015 [18]. It is evident from this that the aviation sector is one of the most crucial sectors that need to strive for GHG emission reduction in order to meet the targets set by the *Paris Agreement*.

Several institutions within the aviation industry have set their own climate targets, which has been earlier touched upon by *Scheers* [15]. *Scheers* presented an overview of the current climate goals from the *National Aeronautics and Space Administration* (NASA) and *Advisory Council for Aeronautics Research in Europe* (ACARE), supported by the earlier work of *Sahoo et al.* [19]. In 2022, ACARE updated their targets by the new initiative *Fly The Green Deal*, which builds upon several earlier initiatives including *Flightpath 2050* [8]. These climate targets are presented in Table 2.1, focusing on NO_x and CO_2 emission reductions goals.

Altogether, the fast growing aviation industry and the ambitious climate targets result in major challenges for aircraft manufacturing companies and large commercial airlines. The industry is required to adopt to cleaner propulsion technologies, increased usage of alternative sustainable fuels and more efficient airline operations and infrastructure in order to meet these challenges [9].

Table 2.1: Climate targets for aviation

Target metric	**NASA N+1**	**NASA N+2**	**NASA N+3**	**Fly The Green Deal**
Year	2015–2025	2025–2035	Beyond 2035	2050
LTO NO_x emissions*	−75%[2]	−80%[2]	−80%[2]	–
Cruise NO_x emissions	−70%[3]	−80%[3]	−80%[3]	−90%[1]
Aircraft Fuel/Energy consumption	−50%[3]	−60%[3]	−80%[3]	–
CO_2 emissions	–	–	–	Net-zero[1]

* LTO = Landing and Take-Off cycle
[1] Relative to 2000
[2] Below CAEP 6
[3] Relative to 2005 best in class

[1]Airbus expects a compounded annual growth rate (CAGR) of 8.4 % until the year 2027 and expects a CAGR of 3.6 % from 2027 until 2043 (similar to the growth pace of pre-COVID) [4].

3

Background on Aircraft Electrification

In the recent years, the aviation industry is in an accelerating transition towards more sustainable modes of air transportation. This shift towards sustainable flight is driven by the pressing demands to reduce emissions in order to meet the climate targets, as previously discussed in chapter 2. The required reduction in total aircraft emissions can be only achieved by the use of alternative fuels and energy resources [5]. In particular, electric and hybrid-electric aircraft have emerged to be an effective solution for reducing these emissions [10–12].

This chapter dives briefly into the current technology of electrified aircraft. First, an overview of the foundation of the growing interest in aircraft electrification is presented in section 3.1. Next, the different aircraft architectures are touched upon in section 3.2, which dives deeper into electrified aircraft configurations and types. Following this, the basics of aircraft battery and recharging technology are discussed in section 3.3. Consequently, two important performance aspects are discussed: section 3.4 and section 3.5 present the mission profile and onboard energy management optimization, respectively. The chapter then provides a brief presentation of previous research into the modeling of the climate impact of electrified aircraft (section 3.6). Lastly, it closes of with a short overview of currently existing and future conceptual electric aircraft in section 3.7. These sections together will provide a concise overview of the electrification of the aviation industry.

3.1 Foundation of Interest in Aircraft Electrification

The interest in the development and use of electrified aircraft is based on six main factors, as outlined by *Schwab et al.* [20] and *Rossow* [21]. This work is supported by a market analysis conducted by *Howell Hanano* [22], a feasibility study of *WSDOT*[1] [23] and the work of *Antcliff* [24]. The analysis resulted in the six main aspects as briefly summarized below:

- **Reduced cost:** The biggest motivator for electrification of aircraft is the projected reduction in cost, resulting in opportunities for currently unprofitable routes. Additional savings in costs come from reduced maintenance, noise, LTO and emissions. An example case, provided by *Schwab et al.* [20], shows that *Ampaire* projects a reduction in fuel and maintenance costs of 90 % and 50 %, respectively.
- **Regional travel market**: Regional air traffic for ranges up to 500 km is a good driver for the increased usage of hybrid-electric aircraft as it provides economical opportunities for regional airports that are currently not being used to their full potential. Consequently, flight accessibility improvements and passenger travel time to airports reductions can be achieved.
- **Emission reduction**: Electrified flight is particularly suitable for lowering the in-flight emissions of short-haul flights.
- **Noise reduction**: Airports are able to achieve substantial noise reductions by the use of electric aircraft due to motor characteristics and flight performance. *Collins Aerospace* predicts a decrease in aircraft noise up to 85 % for all-electric aircraft.
- **Increased accessibility**: Electrified aircraft present the opportunity to alleviate aircraft congestion at busy hubs and major airports. This can be achieved by reducing air traffic in these areas, by allowing short, regional flights to depart, arrive and park at regional airports.
- **Economic development**: The research of *WSDOT* showed that airports and public institutions are mostly interested in investing in the development of underused areas and airports. Additionally, there

[1]Washington State Department of Transportation

is the incentive from aforementioned to stimulate the development of technology and innovation in this area.

In addition to the above mentioned main drivers, there are multiple other beneficial aspects of electrified flight including reduced pilot-training costs, cargo delivery purposes and critical medical services [20].

3.2 Electrified Aircraft Architectures

Over the past few years, there have been technological developments on different types and configurations of electric and hybrid-electric aircraft. There are two important parameters defining electrified architectures: the propulsion configuration and the energy resource type. Based on these two parameters, three main types of electrified aircraft exist: all-electric aircraft, hybrid-electric propulsion (HEP) aircraft and turboelectric. The main difference between conventional and all-electric aircraft is that all aircraft systems are solely supported by an electrical energy source. On the other hand, HEP and turboelectric aircraft use (partly) fossil fuels as the base of their energy source for their propulsion systems. HEP aircraft uses both battery and fossil fuels, while turboelectric aircraft convert fossil fuels into electricity as the energy source for the electrical propulsion systems. The last important aspect of HEP aircraft is their design of the propulsion energy source configuration, where the most dominant distinction is made between two types: series or parallel hybrid. In the former, the batteries provide additional energy to the propulsion system (similar to the turboelectric configuration), while in the latter the propulsion uses of a mix of both battery energy and fossil fuel energy simultaneously. [5, 15, 25, 26]

All-electric and hybrid-electric can be categorized using a concept called the degree of hybridization, which was introduced by *Isikveren* [27]. The degree of hybridization is expressed in terms of the aircraft's power (H_p) and energy resource (H_E) in Equation 3.1 and Equation 3.2, respectively. In both equations, the contribution of the motor power (P_m) and battery energy (E_b) is taken as a fraction of the total power (P_{tot}) and energy resource (E_{tot}), respectively.

$$H_P = \frac{P_m}{P_{tot}} \tag{3.1}$$

$$H_E = \frac{E_b}{E_{tot}} \tag{3.2}$$

The different architectures of electrified aircraft are presented with their corresponding degree of hybridization in Table 3.1, which is modified from a similar overview presented by *Brelje & Martins* [25]. It illustrates the level of electrification and hence the impact of hybridization on the propulsion design of electrified aircraft.

Table 3.1: Classification of electric propulsion architectures, modified from [25]

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

3.3 Battery and Recharging Technology

The adoption of electrified aircraft introduces major challenges related to onboard battery availability and charging technology. According to *Adu-Gyamfi & Good* [28], advancements in battery technology is one of the three critical drivers for the development of the electric aviation industry. Furthermore, *Liang et al.* [5] emphasizes that the recharging infrastructure at airports are under-invested compared to other aspects, such as certification, and that achieving fast recharging remains a significant challenge. This section briefly summarizes the state-of-the-art battery technology, recharging characteristics and a battery swapping strategy in subsection 3.3.1 – 3.3.3, respectively.

3.3.1 Battery Design

In the aviation industry, battery-based electrical energy storage systems (BESS) play a crucial role in achieving the desired aircraft performance. Enhancing battery performance is one of the key drivers of aircraft electrification development. This subsection discusses the key aspects of battery performance and various used battery types in the industry.

Battery Performance Parameters

Several factors influence the battery design and performance, resulting in being one of the critical components of electrified aircraft. The most significant performance parameters[2] for electric aircraft, as outlined by *Liang et al.* [5] and *Zamboni* [29], are the following: gravimetric energy density, power density and volumetric density. These performance parameters have been summarized in Table 3.2 along their corresponding relevance to aircraft performance. An additional key parameter is the *State of Charge* (SoC), which expresses the current state of the remaining capacity as a percentage of the nominal capacity. A *State of Charge* of 0 % and 100 % represent a fully discharged and fully charged battery, respectively [29]. Besides these energy performance parameters, there are other considerations for the integration of batteries in electric-flight. These considerations include the development of thermal management system, battery lifetime optimization, safety measures and certification [5].

The understanding of these key parameters is crucial and forms the foundation for appropriately selecting the battery design and type for electrified aircraft.

Table 3.2: Battery design performance parameters

Parameter	Definition and Application	Units
Gravimetric energy density	The quantity of energy stored per unit of mass (often referred to as specific energy) and gravimetric energy density determines the range and payload of a flight [5, 30]	Wh/kg
Power density	The amount of energy flow per unit mass per unit time (often referred to as specific power) and the power density is the determinant of take-off and climb performance as well as high charging power rates [5, 30]	W/kg
Volumetric energy density	The quantity of energy stored per unit of volume and the volumetric energy density is of high importance for design aspects for the wing and fuselage due to volume limitations [5]	Wh/L

Battery Types

The current market offers a range of battery types with distinct characteristics and performance based on the previously provided parameters. The battery type that is most dominantly used across various industries, particularly in the automotive industry, is the lithium-ion battery (LIB). LIB's are widely used due to their preferred high power and energy density in combination with their long lifespan. These batteries can consist of a combination of various anode and cathode materials, which are presented in tabular form in Table 3.3. Besides NMC-type LIB's, which are expected to have the highest share in the air transportation industry in the coming years, other battery chemistries also show great potential to serve as an energy source in the electrification of aircraft. Post-lithium-ion batteries (PLIB) including solid-state-batteries (SSB), lithium-sulfur-batteries (LSB) and lithium-air-batteries (LAB) are promising due to their high energy density characteristics. The choice of the battery configuration for electrified aircraft design is a trade-off, requiring to balance performance parameters and the latest battery developments in the industry. [5, 31]

3.3.2 Battery Recharging

The recharging of batteries in electrified aircraft is one of the key limitations in the current development as it heavily limits the turn-around-time (TAT) [32]. The optimization and implementation of different charging strategies can help mitigate this limitation, thereby significantly contribute to advancements in the electric aviation industry. However, increasing charging speeds and efficiency comes at the cost of accelerated battery degradation, resulting in a trade-off that must be carefully evaluated. Recently, *Liang et al.* [5] provided an overview of several charging strategies suitable for the electric aviation industry, which are summarized in this subsection.

[2]Note: There are other relevant performance parameters that are not mentioned, but have been touched upon by *Zamboni* [29] and *Antunes* [26].

Table 3.3: Lithium-ion battery anode and cathode configurations

Lithium-ion Batteries			
Anode		**Cathode**	
Iron–phosphate (LFP)	$LiFePO_4$	Lithium–titanate (LTO)	$LiTi_5O_{12}$
Nickel–manganese–cobalt (NMC)	$LiNi_xCo_yMn_zO_2$	Graphite	C
Nickel–cobalt–aluminum (NCA)	$LiNi_xCo_yAl_zO_2$	Silicon	Si
Manganese oxide (LMO)	$LiMn_2O_4$		

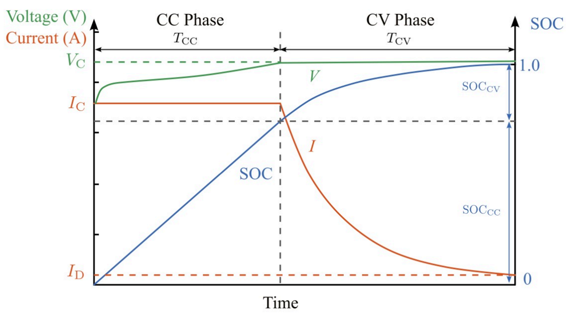
Conventional

The conventional charging strategy is the constant-current constant-voltage (CC-CV) strategy, which is the most widely adopted charging method across various industries due to its simplicity and cost-effectiveness. The charging profile can be distinctly divided into two phaes: a linear constant-current (CC) charging phase that charges up to approximately 80 % of the battery's SoC, followed by a non-linear constant voltage (CV) charging phase from 80 % to 100 %. This charging profile is illustrated by Figure 3.1a. However, this charging strategy has its limitations for applications in electric aircraft, particularly due to its inability to achieve high charging rates in the final 20 % of the charge. [5]

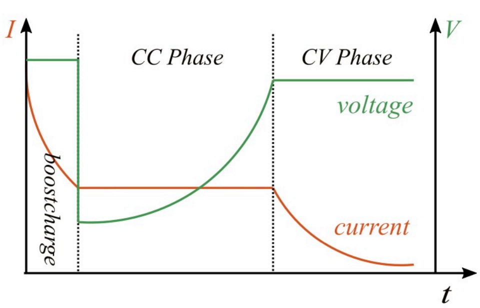
Boost-Charging and Multistage-Charging

Two alternative charging strategies to address the limitations of the CC-CV strategy have been reviewed by *Liang et al.* [5]: the boost-charging CV-CCCV and the multistage CC charging strategies. The former, as proposed by *Notten et al.* [33], uses a three phase charging concept in which high charging speeds are obtained without the negative side effect of high degradation values. As illustrated by the voltage and current curves in Figure 3.1b, this charging initiates a boost after which it is followed by the conventional CC-CV phase. The latter charging strategy, the multistage CC strategy from *Vo et al.* [34], splits the entire charging cycle into multiple CC charging phases as depicted in Figure 3.1c. This results in an improved charging efficiency and a reduced charging time up to 22.5 % compared to the conventional CC-CV strategy.

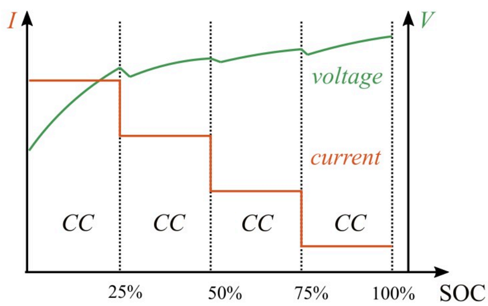
These two strategies highlight the importance of innovative charging methods for the electric aviation industry, as they can significantly reduces charging times and thus achieve shorter TAT requirements.



(a) Conventional CC-CV



(b) Boost-charging CV-CCCV



(c) Multistage CC

Figure 3.1: Schematic representation of three charging strategies [5]

3.3.3 Battery Swapping Strategy

An alternative solution to address the challenges of the charging speed limitations for the TAT is battery swapping, as proposed, among other researchers, by *Justin et al.* [32]. In his work, the additional benefits of a battery swapping strategy are emphasized, including cost minimization through adequate timing and low power levels, increased energy availability during high demand periods, and enhanced cooling capabilities. The optimization of both recharging and battery swapping resulted in reductions of peak-power draw and electricity cost of 61 % and 25 %, respectively. This paper demonstrates the potential of alternative solutions to address these electrified aviation challenges, emphasizing the importance of integrating advanced technologies to further support the development of the electrified aviation industry.

3.4 Mission Profile of Electrified Aircraft

The mission profile of hybrid-electric aircraft is a crucial factor of influence to both aircraft performance and design considerations. Generally, the aircraft mission profile comprises five main phases: taxi, climb, cruise, descent and potential diversion [5, 35–37]. A detailed visual representation of these flight phases is provided in Figure 3.2. There are several key aspect related to the mission profile of electrified aircraft: mission profile optimization, fuel requirement considerations and range estimation techniques.

This section briefly touched upon these three mission profile aspects. First, a mission profile optimization with respect to the propulsion energy source is presented in subsection 3.4.1. This is followed by an overview of the current fuel requirements for flight in subsection 3.4.2. Lastly, subsection 3.4.3 dives into two range estimation methods for electrified aircraft. These subsections together present a brief yet comprehensive overview of the basic mission profile aspects of electrified flight.

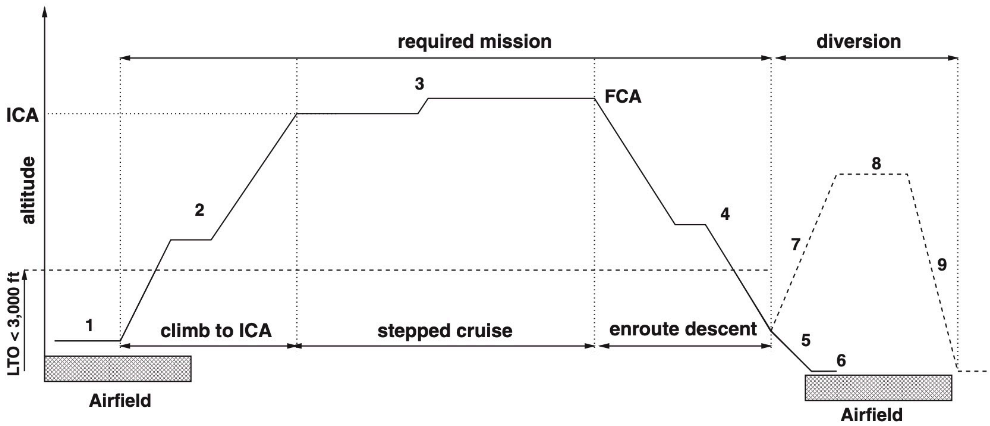


Figure 3.2: Standard mission profile of passenger aircraft [36]

3.4.1 Mission Profile Optimization

Several research has been conducted into the mission performance of hybrid-electric aircraft. For instance, the study from *Palaia & Salem* [37] analyzed the mission performance analysis of regional hybrid-electric aircraft by integrating the pre-determined distribution of propulsive energy resource across the entire mission profile. A detailed mission profile for hybrid-electric aircraft[3] with corresponding propulsion selection, developed by *Palaia & Salem* [37], is visually represented in Figure 3.3. In this figure, the use of battery energy and a thermal energy source is indicated by the colored line green and red, respectively.

The study by *Palaia & Salem* optimizes for a general flight scenario without diversion requirements and therefore distributes all battery energy across the normal mission phases. This approach focuses on maximizing aircraft sustainability by minimizing flight emissions, according to the rationale presented by *Perullo & Mavris* [38]. Consequently, the thermal energy source is reserved for the diversion phase as sole source of energy, adhering to predetermined fuel requirements.

Furthermore, this study assumes that during take-off, climb and cruise phases, always a combination of power

[3]The hybrid-electric aircraft has an parallel-hybrid configuration.

sources is necessary to achieve required thrust levels. During taxiing, the sole energy source of battery energy is assumed to minimize local emissions at airports. In conclusion, this research emphasizes the importance of the optimal allocation of energy resources across the flight phases to enhance performance and climate impact.

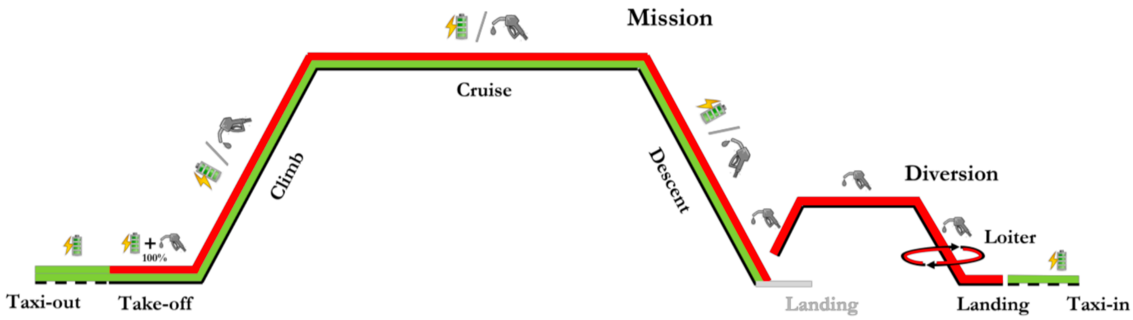


Figure 3.3: Mission profile with a scheme of selected power supply strategy [37]

3.4.2 Fuel and Battery Requirements

Electrified aircraft, similarly to conventional aircraft, need to adhere to fuel requirements for various phases of their mission profile, as previously discussed in subsection 3.4.1. These fuel requirements influences dominantly the development of mission profiles and design of newly electrified aircraft. Currently, the regulations for electrified aircraft do not specify other fuel requirements for electrified aircraft and therefore the requirements for conventional aircraft provide a good foundation [39]. The ICAO has specified the fuel requirements for conventional aircraft in *Annex 6 – Operation of Aircraft* of the International Standards and Recommended Practices [40]. An earlier overview of the fuel requirements for design and regulations purposes, corresponding to *Annex 6 – Operation of Aircraft* of the ICAO, was presented by *Mukhopadhaya & Graver* [39]. These most important fuel requirements are listed below:

1. It needs to account for an contingency fuel of 5 % of the total planned trip fuel (*Annex 6 section 4.3.6.2c*).
2. There must be sufficient fuel to reach an alternate destination airport within 100 kilometers (comparable to *Annex 6 section 4.3.6.2d*).
3. It needs to have sufficient reserve fuel to loiter for a period of 30 minutes (*Annex 6 section 4.3.6.2e*).

Based on these three main fuel requirements, *Mukhopadhaya & Graver* formulated the aircraft's operational cruise range (R_{OC}) by Equation 3.3.

$$R_{\mathrm{OC}} = (1 - \mathrm{SOC}_{\mathrm{cont}})\,(R_{\max} - R_{\mathrm{alt}} - v_{\mathrm{l}} \cdot t_{\mathrm{l}}) \tag{3.3}$$

3.4.3 Range Estimation Techniques

There are several methods for estimating the range for electrified aircraft, as recently touched upon by *Antunes* [26]. This work outlined the two most used methods for electrified aircraft are the energy-based method and the modified Breguet range equation developed by *Finger et al.* [41] and *De Vries* [42], respectively. This subsection provides a brief summary of both methods, which form the foundation for range estimations and addresses reverse hybridization factor considerations.

Energy-Based Method

The energy-based method evaluates the required energy over a planned flight trajectory by dividing it into multiple discrete time steps. For each of time step, the energy demand is calculated on various energy components. *Finger et al.* focuses on the following three energy components: aerodynamic drag, kinetic energy and potential energy. Equation 3.4 formulates the relation for the total required energy based on these three factors. This equation can be extended by adding factors that influence the energy consumption of specific flight phases or operational aspects. For example, the required energy for taxi movements at the airport pre- and post-flightcan be approximated by the energy demand for rolling resistance. *Finger et al.* used the energy-based equation to compute the total power required for each time step of the flight, and the fuel and battery mass (taking burned fuel into account). The required fuel and battery mass functions are provided in Equation 3.5 and 3.6, respectively. The total mass of the fuel of the internal combustion engine and the battery can then be determined by the summation of all time step. [41]

$$\Delta E = \underbrace{\frac{m \cdot g \cdot v}{(L/D)} \cdot \Delta t}_{\Delta E_{\text{Aero.Drag}}} + \underbrace{\frac{m \cdot \Delta v^2}{2}}_{\Delta E_{\text{Kinetic}}} + \underbrace{m \cdot g \cdot \text{ROC} \cdot \Delta t}_{\Delta E_{\text{Potential}}} + \dots \tag{3.4}$$

$$\Delta m_{\text{fuel,ice}} = (1 + \text{tf}) \cdot P_{\text{ice}} \cdot \text{NOD} \cdot \text{BSFC} \cdot \Delta t \tag{3.5}$$

$$\Delta m_{\text{Battery}} = (1 + \text{DDP}) \cdot \frac{\Delta E_{\text{nc}}}{\eta_{\text{BtT}} \cdot E_{\text{Battery}}} \tag{3.6}$$

Modified Breguet Range Equation

The Breguet range equation, typically used for conventional aircraft, was modified for hybrid-electric and all-electric aircraft by *De Vries* [42, 43]. *De Vries* developed an adjustment of the Breguet Range equation that is applicable for conventional, hybrid-electric and all-electric aircraft by incorporating a constant supplied power ratio (Φ). This formulation focuses on the flight cruise phase and hence can be only applied on mission profiles with dominant cruise phases. The complete modified range equation from *De Vries* is provided in Equation 3.7[4]. This equation is slightly reduced for the limit cases of conventional ($\Phi = 0$) and all-electric ($\Phi \to 0$) [42, 43]. Consequently, it can be derived back to the original range equation for conventional and all-electric aircraft provided by Equation 3.8 and 3.9, respectively.

$$R = \eta_3 \frac{e_f}{g} \left(\frac{L}{D}\right) \left(\eta_1 + \eta_2 \frac{H_E}{1 - H_E}\right) \ln \left[\frac{W_{OE} + W_{PL} + \frac{g}{e_{\text{Bat}}} E_{0,\text{tot}} \left(H_E + \frac{e_{\text{Bat}}}{e_f}(1 - H_E)\right)}{W_{OE} + W_{PL} + \frac{g}{e_{\text{Bat}}} H_E E_{0,\text{tot}}} \right] \tag{3.7}$$

$$R = \eta_{gt} \eta_p \left(\frac{L}{D}\right) \left(\frac{e_f}{g}\right) \ln \left[\frac{W_{OE} + W_{PL} + W_f}{W_{OE} + W_{PL}}\right] \tag{3.8}$$

$$R = \eta_{em} \eta_p \left(\frac{L}{D}\right) \left(\frac{e_{\text{Bat}}}{g}\right) \left(\frac{W_{\text{Bat}}}{W_{OE} + W_{PL} + W_{\text{Bat}}}\right) \tag{3.9}$$

3.5 Hybrid-Electric In-Flight Energy Management

The use of hybrid-electric aircraft introduces an additional challenge due to the degree of freedom as an additional variable during flight. *Leite & Voskuijl* [44] emphasizes that HEP aircraft need to manage and optimize the consumption rate of two energy sources, compared to a single thermal energy in conventional aircraft. Most HEP aircraft are equipped with an available automatic controller onboard that is designed to manage real-time energy usage from both resources. Generally, there is *a priori* information available for the flight and *Leite & Voskuijl* uses this information for optimal control of energy management over the flight.

An additional feature that *Leite & Voskuijl* highlight in their optimal energy management is the potential to recharge the battery *State of Charge* during specific flight phase, such as the descent. The availability of an electric motor in combination with a propeller can serve both battery recharging and speed braking purposes. The maximum power available for battery recharging can be calculated by using of the wind power equation proposed by *Kalmikov* [45] (Equation 3.10). The maximum power that can be harvested for a given speed ($P_{w,max}$) in this equation depend on the air density (ρ), rotor area (A_r), the wind speed (V_w) and power coefficient (C_P). The C_P value is assumed to have a value < 0.3, as its propellir design has not been optimized for recharging purposes.

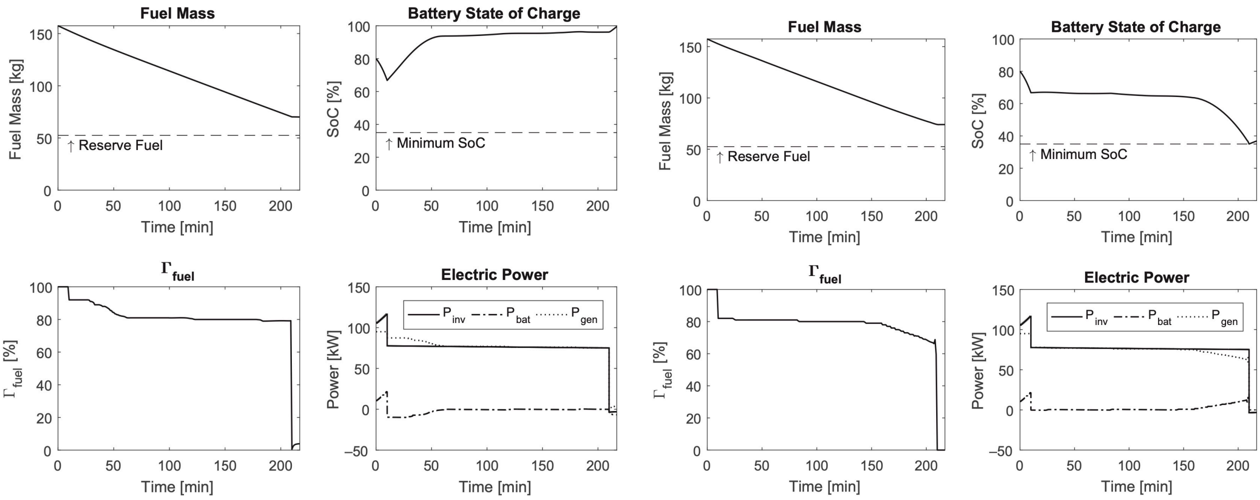
$$P_{\text{w,max}} = \frac{1}{2} \cdot \rho \cdot A_r \cdot V_w^3 \cdot C_P \tag{3.10}$$

Leite & Voskuijl utilized the concept of in-flight recharging to develop two optimal energy control strategies

[4] The supplied power ratio (Φ), as defined in *De Vries*'s original work [42, 43], is substituted with the degree of hybridization (H_E).

for HEP aircraft. The first aims at constraining the final battery SoC (up to 100 %), while the second strategy considers the SoC to be unconstrained (free) at the end of the flight. The optimal battery usage over cruising follows the principle proposed by *Perullo and Marvis* [38], which prioritizes depletion of fossil fuel as energy source and delaying battery usage until later in the flight. This approach follows the rationale that depletion of fossil fuel, unlike the battery, results in a a reduced aircraft weight, becoming more efficient as the flight progresses. The unconstrained and constrained optimal energy control solutions developed by *Leite & Voskuijl* are visualized in Figure 3.4a and 3.4b, respectively. Each figure consists of four time-series diagrams with fuel mass, battery SoC, generator throttle setting (Γ_{fuel}) and electric power. A significant drop in the battery SoC is observed at the start of the flight in both figures, which is a result of the high energy demand of the climb phase.

The work described above emphasizes the challenges that are introduced by the additional degree of freedom in hybrid-electric aircraft brings. Furthermore, it presents the opportunity and flexibility for optimal energy management in battery-constrained scenarios.



(a) Unconstrained battery energy control solution (to 100 %)

(b) Unconstrained battery energy control solution

Figure 3.4: Visualization of the two optimal in-flight energy control solutions for hybrid-electric aircraft developed by *Leite and Voskuijl* [44]

3.6 Climate Impact of Electrified Aircraft

The electrification of aircraft, along with synthetic fuel and hydrogen-powered aircraft alternatives, can significantly reduce emission, thereby contributing to the earlier discussed climate targets and advancing the decarbonization of the aviation sector [13, 14]. All-electric aircraft eliminate direct flight emissions, while hybrid-electric aircraft allow for substantial reductions compared to conventional aircraft. However, actual emissions from hybrid-electric aircraft depend on degree of hybridization, design features and operational aspects.

A number of studies have been conducted focused on the modeling of aircraft emissions and the ability of quantifying their environmental impact. These analysis are often based on emission indices of pollutants to support effective radiative forcing (ERF) and radiative forcing (RF) calculations for the climate impact of aviation. For instance, *Lee et al.* [46] incorporated the emission indices of CO_2, NO_x, Water Vapor, Soot and SO_2 into ERF and RF. Additionally, *Scheers* [15] provided an overview of hybrid-electric aircraft emissions for both flight and ground operations. The carbon emission indices for hybrid-electric aircraft are split up in three categories: kerosene flight and ground emissions, and electricity ground emissions.

The overview of the emission indices obtained from *Lee et al.* and *Scheers* are presented in Table 3.4a and 3.4b, respectively. This data provides the basis for the assessment of electrified aircraft's environmental impact.

Table 3.4: Emission Indices for Fuels and Pollutants

(a) Emission indices for various pollutants

Pollutant	Emission Index[1]
CO_2	3.16
NO_x	0.01514
Water Vapor	1.231
Soot	0.0003
Sulfur (SO_2)	0.0012

[1] Emission expressed in kg/kg fuel

(b) CO_2 emission indices for kerosene and electricity

Emission	CO_2 Emission Index
Kerosene (flight conditions)	3.155[1]
Kerosene (ground conditions)	0.47822[1]
Electricity (ground conditions)	0.03001[2]

[1] Emission expressed in kg CO_2/kg fuel
[2] Emission expressed in kg CO_2/kWh

3.7 Current and Future Electrified Aircraft

The development of electrified aircraft is growing over the past few years and different concept are designed for various purposes. *Schwab et al.* [20] categorized the different use cases of future electrified aircraft into three time segments: near-term (2020-2025), mid-term (2025-2040) and long-term (2040-2050). The near-term development is focused on pilot training and personal and business aviation for small amount of passengers. The focus in the mid-term developments lies with regional air transportation and light air cargo. The long-term aviation is focusing on larger commercial aircraft with a capacity over 150 passengers. An adjusted overview of the different use cases of each time segment with corresponding conceptual aircraft models are presented in Table 3.5.

An overview of the characteristics of selected electrified aircraft, along with their corresponding expected year of entry into service (EIS), is provided by *Liang et al.* [5]. This overview presents the key statistics of electrification programs[5], the details are summarized in Table 3.6.

Table 3.5: Timeline for electric and hybrid-electric aircraft development, modified from [5]

Timing	Use Case	Description	Model
2020-2025 *Near-term*	General aviation: personal or business	– 1-6 passengers – Average flight time: < 1 h	– Pipistrel Taurus Electro – Rhyxeon General Aircraft RX4E
2025-2040 *Mid-term*	Regional aircraft	– Typical up to 19 passengers – Range typically around 250 miles	– Eviation Alice – Tecnam P-Volt – Aura Aero ERA – Heart Aerospace ES30 – Ampaire Electric EEL[1] – Maeve 01
2040-2050 *Long-term*	Large commercial aircraft	– Narrow-body: typically 100-200 passengers, range more than 500 miles – Wide-body: typically 200-400 passengers, range more than 2000 miles	– Wright Spirit – Wright 1 – Boeing Sugar Volt[1] – NASA N3-X[2] – Airbus/Siemens/Rolls-Royce/E-Fan X[1]

[1] Hybrid-electric
[2] Turboelectric

[5]Note: The presented information is based on projections and may be subject to change.

Table 3.6: Key specifications of electric aircraft, modified from [5]

Model	Propulsion	Battery Capacity [1]	Maximum Power	Range Endurance	Charging power	Seats	EIS
Pipistrel Velis Electro	All-electric	24.8 kWh	57.6 kW	50 min[2]	80 min	2	2020
Archer Maker	All-electric	75 kWh	672 kW	60 miles	133.2 kW[3]	2	2024
Joby S4	All-electric	200 kWh	N.A.	150 miles	N.A.	4	2024
Airbus CityAirbus	All-electric	110 kWh	N.A.	50 miles	N.A.	4	2025
Beta ALIA-250c	All-electric	N.A.	N.A.	288 miles	50 min	6	2024
Lilium Jet	All-electric	305 kWh	N.A.	162 miles	30 min	7	2024
Eviation Alice	All-electric	820 kWh	260 kW	288 miles	30 min	11	2027
Maeve 01	All-electric	2950 kWh	1.6 MW	288 miles[2]	4.5 MW	44	2029
Wright 1	All-electric	N.A.	N.A.	800 miles	N.A.	186	2030
Boeing Sugar Volt	Hybrid-electric	N.A.	1 MW	4028 miles	N.A.	154	2035
NASA N3-X	Turboelectric	N.A.	50 MW	8630 miles	N.A.	300	2045

[1] Nominal capacity
[2] Plus VFR (Visual Flight Rules) reserve
[3] Estimated based on: 30% of the battery capacity is designed to be recharged in 10 min

4

Airline Planning Operations

The aviation industry operates as a complex, large scale network where airlines have to face challenges such as high cost and low profit margins. Airlines must efficiently execute airline operations in order to ensure overall profit maximization. Since the 1960's operational research has been implemented to enhance key aspects of airline operations by using mathematical models to solve smaller sub-problems. Therefore, airlines are required to find more innovative solutions and further integrate operational research to improve its overall performance. [47]

This chapter provides a comprehensive introduction to the airline planning process, including various optimization models and relevant past literature. It starts with a brief introduction into the key elements of the airline planning process in section 4.1. Following this, section 4.2 provides the fundamentals of scheduling optimization models. Consequently, a concise summary of the mathematical optimization solving methods is presented in section 4.3. The chapter closes of with a brief review of past variations of airline scheduling models, provided in section 4.4.

4.1 Introduction to the Airline Planning Process

Airlines face operational challenges within the airline planning process. *Belobaba et al.* [48] outlines the these challenges and divides it in three main phases as formulated below:

- **Fleet planning:** Sizing and composition of the aircraft fleet of an airline, focusing on decisions based on aircraft type and their quantity.
- **Route planning:** The construction of profitable aircraft routes that maximizes revenue and minimizes operational costs.
- **Schedule development:** The development of profitable flight schedules consisting of the following optimizing sub-objectives:
  - **Frequency planning:** The frequency of flight operations on pre-determined routes by an airline.
  - **Timetable development:** The development of a time schedule including all flight to be operated by an airline.
  - **Fleet assignment:** The assignment of specific aircraft types to the flights legs from the developed timetable.
  - **Aircraft rotation planning:** The overall planning of a specific aircraft type ensuring an airport balance constraint of arriving and departing aircraft.

These phases are visually summarized in Figure 4.1, which provides an schematic overview of the entire airline planning process. This overview makes a distinction on short versus long term time horizon and strategic and tactical decision.

This section focuses on the primary long term, strategic planning phases, neglecting all short term phases beyond *schedule development*, as defined by *Belobaba et al.* [48]. The general process of airline fleet planning and aircraft routing is briefly outlined in subsection 4.1.1 and 4.1.2. Consequently, the schedule development phase is extensively evaluated in subsection 4.1.3 as it integrates key aspects of current planning models used by airlines.

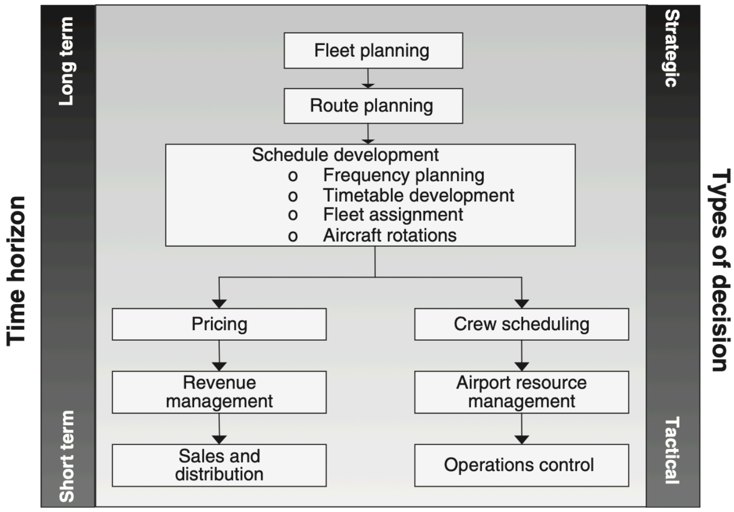


Figure 4.1: Schematic overview of the airline planning process [48]

4.1.1 Fleet Planning

The planning of an airline's fleet is a long-term strategic challenge influencing other operational aspects and hence is a crucial step in the operational performance of an airline. *Belobaba et al.* [48] defines an airline fleet as:

> *The total number of aircraft that an airline operates at any given time, as well as by the specific aircraft types that comprise the fleet.*

The main consideration in an airline fleet sizing process are payload and range characteristics of aircraft types. These characteristics are often represented by a payload-range curve (also referred to as the payload-range diagram), which is shaped by performance and design parameters including aerodynamic properties, engine technology and other limiting design factors. The main objective is to synchronize these aircraft characteristics as best as possible to the expected distance and passenger demands needed to be served. In addition, other constraining aspects need to be incorporated, which include airport limitations such as runway length, gate accessibility, taxiways and ground equipment.

4.1.2 Route Planning

Airline route planning is a critical long-term strategic step that follows from the airline fleet planning process. This phase involves selecting specific routes to be operated with the objective to maximize profitability. Generally, airline route planning is executed after fleet planning, but this sequence can be reversed when fleet sizing is based on pre-determined routes. The primary objective of route planning is to identify and prioritize the most financially profitable routes.

A key consideration in route planning is the distinction between two types of flight networks: point-to-point and hub-and-spoke. Point-to-point networks involve direct flights between origin and destination airports, often accompanying shorter flights involving smaller airports and airlines. In contrast, hub-and-spoke networks allow more centralized operations through hub airports, incorporating transfer flights. Each type of network has its unique advantages and limitations and should be carefully evaluated based on an airline's operational goals.

4.1.3 Schedule Development

The four main sub-objectives that are part of the airline schedule development as presented in this section's introduction will be briefly discussed below. The order of which these tasks are executed by an airline are in a top-down order as they have been itemized.

Frequency Planning

This step involves the determination of the frequency that the flight routes, obtained by the routing planning step, need to be operated by the airline. Effectively performing frequency planning results in better passenger convenience and a better market share of the airline as a result of more frequent flights. Furthermore, frequency planning is closely related with fleet assignment as airlines need to optimize their aircraft size and amount to capture as much passenger demand as possible.

Timetable Development
The assignment of flight to routes at a given time is a crucial step in flight scheduling and requires a trade-off between aircraft utilization and passenger convenience. Several other factors constrain the timetable development, which include TAT, arriving time restrictions, crew scheduling considerations, and maintenance requirements. The complexity of the timetable development often results in significant challenges, as deviations from the initial model can lead to sub-optimal outcomes.

Fleet Assignment and Aircraft Rotations
The fleet assignment step follows after the creation of the timetable and assigns an aircraft type to a flight leg from the timetable. The main objective is to minimize operational cost while also minimizing the amount of spilled demand, i.e. maximizing the revenue obtained from the served demand. Airlines generally have their own optimizing fleet assignment models, which optimize to serve the demand as best as possible as there is no perfect alignment between airline fleet seat capacity and the demand.

4.2 Airline Scheduling Optimization Model

Building upon the airline planning processes, as outlined in section 4.1, this section introduces airline scheduling optimization models. These models aim to develop profit-maximizing flight schedules, while adhering to provided operational constraints. *Barnhart & Vaze* [48] splits the airline schedule optimization problem up in four sequential sub-problems that are ought to be solved in a top-down approach:

1. **Schedule design problem:** The design of an airline flight schedule by integration of flight legs between departing and destination airports.
2. **Fleet assignment problem:** The optimal assignment of aircraft types to satisfy demand over flight legs ensuring an profit-maximizing objective.
3. **Maintenance routing problem:** The assignment of specific aircraft, identified by their tail numbers, to flight legs while satisfying availability constraints. Generally, this step builds further on the outcomes ofthe fleet assignment problem.
4. **Crew scheduling problem:** The assignment of pilots and cabin crew to the determined flight schedule, while focusing on cost-minimization objectives.

The main two problems of interest that arise form these sub-problems are the Fleet Assignment Problem (FAP) and the Aircraft Routing Problem (ARP), which are presented and supported in subsection 4.2.1 and 4.2.2, respectively.

4.2.1 Fleet Assignment

The fleet assignment model (FAM) has been recently defined by *Birolini et al.* [49] with the following objective:

> *Fleet assignment is about assigning appropriate fleet types to each flight leg such that seat capacity optimally matches the expected demand, subject to resource balance constraints in the network.*

The fleet assignment problem initially focused on designing a profitability function that determined the optimal assignment of an aircraft type to a specific flight leg. Even though it was able to identify the most profitable routes, the assignment led to infeasible solutions as it failed to incorporate aircraft balance constraints.

This aircraft imbalance problem was solved as *Hane et al.* [50] introduced time-space networks into the FAM, as visualized in Figure 4.2. The time-space network is divided by two different arc types: a flight arc and a ground arc. The former is a space-time vector representing a specific flight leg, based on four parameters: departure time, departure location, arrival time and arrival location. Additionally, the minimum TAT is often included in the flight arc, resulting in longer flight time than the true flight time [48, 51]. The ground arcs in the time-space network represent the duration an aircraft spends on the ground, including ground operations. The time-space networks approaches the FAM by evaluating the temporal and spatial dimensions simultaneously ensuring balance constraints, while optimizing fleet assignment.

The example time-space network in Figure 4.2 illustrates an optimal scheduling and fleet assignment. In this figure, the set of flight arcs are indicated in green with corresponding specific flight numbers and assigned aircraft types in bold. The network ensures aircraft balance for all flight legs and fleet types.

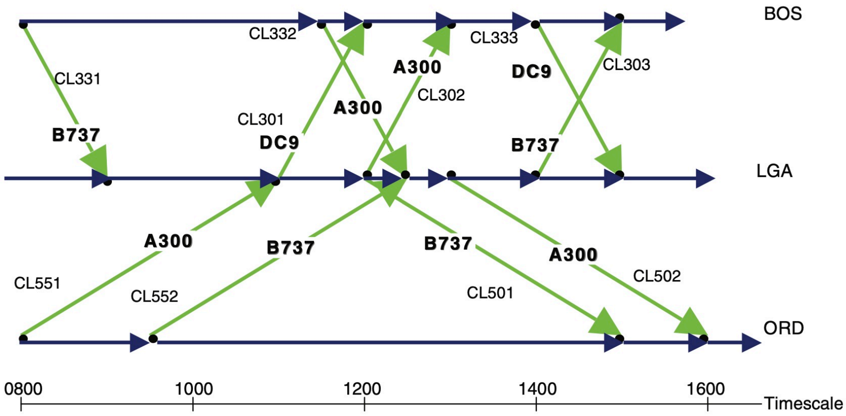


Figure 4.2: A space-time network representing the optimal fleet assignment of an example fleet assignment problem [48]

The resulting mathematical formulation of basic fleet assignment model, as developed by *Hane et al.* [50], is presented below. The objective is defined as a minimization of operating cost rather than a maximization function, where the cost of a flight is calculated as the operating cost minus total revenue. The cover, balance and aircraft availability constraints are represented in the mathematical model by the constraints in Equation 4.1b - 4.1d, respectively [52]. For clarification, this formulation follows a Mixed-Integer Linear Programming (MILP) approach, as discussed in subsection 4.3.1. This basic fleet assignment model has served as the foundation for the development of more complex models with additional constraints and multi-objective functions.

Basic Fleet Assignment Model

$$\text{minimize} \quad \sum_{i \in F} \sum_{k \in K} c_i^k f_i^k \tag{4.1a}$$

$$\text{subject to} \quad \sum_{k \in K} f_i^k = 1, \qquad \forall i \in F, \tag{4.1b}$$

$$y_n^k + \sum_{i \in O(k,n)} f_i^k - y_n^k - \sum_{i \in I(k,n)} f_i^k = 0, \qquad \forall n \in N^k, \forall k \in K, \tag{4.1c}$$

$$\sum_{a \in CG(k)} y_a^k + \sum_{i \in CL(k)} f_i^k \leq M^k, \qquad \forall k \in K, \tag{4.1d}$$

$$f_i^k \in \{0, 1\}, \quad \forall i \in F, \forall k \in K, \tag{4.1e}$$

$$y_a^k \geq 0, \qquad \forall a \in G^k, \forall k \in K. \tag{4.1f}$$

4.2.2 Aircraft Routing

After the successful development of a flight schedule design and a fleet assignment, the next step includes determining the specific route each aircraft will operate. The aircraft route needs to adhere to a variety of constraints including block hours (total accumulated flight hours), number of take-off and landings, maintenance requirements. A common approach to solving the aircraft routing problem is to divide the network into smaller sub-networks based on fleet types and solve independently. The ultimate objective is to ensure that every flight leg has assigned a single aircraft to it, while ensuring that each aircraft begins and ends it route at the same location. [47, 48]

4.3 Optimization Solving Methods

There are several optimization techniques used for solving optimization problems in airline planning and the following two are widely used: Mixed-Integer Linear Programming (MILP) and Dynamic Programming (DP).

This section provides a brief overview of the functionality of both methods in subsection 4.3.1 and 4.3.2, respectively. Additionally, a model comparison is presented in subsection 4.3.3, focusing on the applicability to airline planning operations.

4.3.1 Mixed-Integer Linear Programming

Mixed-Integer Linear Programming (LP) builds upon the principle of linear programming, which has been extensively discussed and outlined by *Dantzig* [53] in 1963. LP is an optimization technique aiming at maximizing or minimizing a linear objective function, while being subjected to a set of linear equality and inequality constraints [54]. LP adheres to the following assumptions (axioms), as reviewed by *Dantzig and Thapa* [55]: proportionality, additivity and continuity.

The formal mathematical formulation of a minimization and maximization LP in matrix form, obtained from *Dantzig and Thapa* [55], is represented by Equation 4.2 and 4.3, respectively. The LP contains decision variables, which are variables that are unknown, commonly nonnegative and require optimization [56]. The current mathematical formulation considers only equality relations for the constraints in Equation 4.2b and 4.3b, but these can be converted in inequality constraints depending on the system.

$$
\begin{aligned}
\underset{x}{\text{minimize}} \quad & c^\top x && \text{(4.2a)} \\
\text{subject to} \quad & Ax = b, && \text{(4.2b)} \\
& x \geq 0 && \text{(4.2c)}
\end{aligned}
\qquad\qquad
\begin{aligned}
\underset{x}{\text{maximize}} \quad & c^\top x && \text{(4.3a)} \\
\text{subject to} \quad & Ax = b, && \text{(4.3b)} \\
& x \geq 0 && \text{(4.3c)}
\end{aligned}
$$

The MILP is an extension of LP by allowing decision variables to be of binary, integer or continuous kind, while LP only accomodates continuous values [56]. This advanced flexibility of MILP makes it more suitable for solving complex optimization problems compared LP. The Simplex method, developed by *Dantzig*, is a commonly used approach for solving MILP problems [53, 55]. Another method for solving MILP problems is the Branch-and-Bound algorithm, offering a alternative strategy [57].

4.3.2 Dynamic Programming

Dynamic programming is a mathematical technique, developed by *Bellman* [58] in 1954, for solving large complex sequential decision processes. The creation of the dynamic programming theory came forth from the study into several multi-stage decision procession. The fundamental basis of dynamic programming lies in *Bellman's Principle of Optimality* [58, 59], which has been formulated as follows:

> *An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision*

This principle leads to the following dynamic programming characteristics as described by *Hillier & Lieberman* [57]. The larger problem can be separated into a set of stages, each with required policy statement. Each of these stages include corresponding states related to the initial conditions of that stage. Then the decision policy is required to ensure that the current state is adapted to a specified state corresponding to the beginning of the next stage. By the application of this objective, an optimal policy for all the stages is achieved and hence an optimal policy for the entire problem. One important aspect is that based on the current state the optimal policy for all future stages is not dependent on made decisions in earlier stages. Generally, the problem can be solved using two variations: forward or backward iteration. In the backward iterative approach, the final stage is considered as the initial stage to be evaluated, whereas in the forward iterative approach the initial stage is considered. The decision on forward and backward iterative approach is dependent on the type of problem. Generally, backward propagation is computationally preferred over forward propagation due to its nature as it requires to consider less outcome scenarios [58].

Contrarily to LP, dynamic programming does not include a standard mathematical formula that is applicable to all problems. Dynamic programming is often identified as an approach structure for solving a large variety of problems. The main approach, as extensively described by *Hillier and Lieberman* [57], is to divide the problem in simpler, solvable smaller sub-problems and solve these sub-problems to optimality. It gradually increases the size of the problem, finding optimal solutions based on the optimal results of the connected sub-problem. However, there is a mathematical relation that is often used for the approach and definition of dynamic problems. The typical dynamic programming formulation, a recurrence relation, is in the form of Equation 4.4 (forward iterative approach). In this formula, $f_N(S)$ describes the value from a N-stage process using optimal policy, $R(S,P)$ is the reward value of the decision S for state P, and $f_{N-1}(S)$ is the value of the previous stage based on the update state $S'(P)$. The backward iterative approach is formulated by a small adjustment in the stage relation by changing the inclusion of the previous stage to the future stage as provided in Equation 4.4.

$$f_N(S) = \max_P \left[R(S,P) + f_{N-1}(S'(P)\right] \tag{4.4}$$

$$f_N(S) = \max_P \left[R(S,P) + f_{N+1}(S'(P)\right] \tag{4.5}$$

4.3.3 Model Comparison

The two previously discussed solving models, MILP and DP, offer distinct advantages and limitations for specific airline planning models. These methods, focusing on their applicability to the fleet assignment and aircraft routing problem, have been extensively reviewed by *Antunes* [26] in 2024. This review dived into various earlier studies and outlined the performance of MILP and DP across several indicators. Additionally, it emphasized the dominant use of MILP in airline planning models. This subsection provides a concise overview of relevant key features and considerations of each model.

Mixed-Integer Linear Programming

Mixed-integer linear programming, as the name implies, is generally best suited for large, fully-linear models and has demonstrated superior performance over dynamic programming in certain applications [60, 61]. MILP is utilized for a wide variety of applications in airline planning problems, as outlined by *Antunes* [26]. Although MILP has wide applications for solving complex models, it is inherent limitedly by its linear formulation and solving nature.

Challenges arise when nonlinear relationships are present problems required to be solved using MILP, which can be addressed by two approaches. First, mixed-integer nonlinear programming (MINLP) model can be developed, which integrates the nonlinear constraints and objective function, but introduces more challenges due to its complexity, nonlinearity, non-convexity and large number of variables. The other approach involves linearizing the nonlinear relations of the problem in order to enable being reformulated as a MILP. The linearization process often results in complex structures and requires assumptions or uncertainties to be incorporated in the model. [61]

Furthermore, another limitation arises from the solving nature of MILP, which requires the model to evaluate the entire system instantaneous. For scheduling problems, this means that the entire time horizon needs to be analyzed at once, resulting in computationally exhaustive process due to the large amounts of constraints and variables [61]. However, MILP offers the advantage of being solved by advanced, high speed commercial solvers, including CPLEX and Gurobi. [61]

In conclusion, MILP is a powerful and widely adopted solving technique in airline planning, particularly for solving linear problems that are not computationally manageable to evaluate within a single framework.

Dynamic Programming

Dynamic programming is well-suited method for attaining optimal solutions in optimization problems that include state-dependent features or separable problems that can divided into smaller sub-problem. The multi-stage structure of dynamic programming can accommodate non-linear elements, allowing it to address also non-linear problems. Although not as widely adopted as MILP in airline planning, it remains a fundamental solving technique of growing interest across various areas due to increased computational power in recent decades [62].

Similarly to MILP, dynamic programming also poses certain limitations. A major limitation of dynamic programming is that is suffers heavily from its own *curse of dimensionality*, a term introduced by Bellman [63]. It refers to the exponential increase in problem size as an extra dimension is added to the system. Multiple strategies have been developed on mitigating these effects, as extensively discussed by *Li et al.* [63]. Despite these mitigation, dynamic programming remains most efficient for problems with a relatively small number of sub-problems as the overall problem size tends to expand quickly with additional sub-problems [62].

In conclusion, DP is a strong optimization technique for solving complex, separable problems with its ability to address non-linearity and to incorporate state-dependent decisions.

4.4 Airline Planning Models

Over the past decades, numerous airline planning models have been developed, including more complex aspects of airline planning operations. Some of these models have been extensively reviewed by *Sherali et al.*[52] and *Birolini et al.* [49]. Additionally, *Birolini et al.* emphasizes the advantages of integrating flight scheduling and fleet assignment models to simultaneously couple the selection of flight legs and allocation of aircraft types.

A comprehensive summary of several extensions to basic model and integrated airline planning models is presented in Table 4.1.

Table 4.1: Overview of literature on the development of airline planning models

Author	**Year**	**Description**	**Reference**
Barnhart et al.	1998	An integrated fleet assignment and aircraft routing model incorporating capture costs of aircraft connections and adhering to maintenance requirement constraints.	[64]
Rexing et al.	2000	An integrated flight scheduling and fleet assignment model including flexibility in flight departure times by means of using time windows.	[65]
Barnhart et al.	2002	An itinerary-based fleet assignment model (IFAM) that is an integration of the FAM and passenger mix flow (PMF) model, developed by *Kniker et al.*. This IFAM introduces new decision based on spill and recapture, along with their corresponding costs. The model is built upon the work from *Farkas*, which does not include recapture features.	[66–68]
Lohatepont & Barnhart	2004	An integrated flight schedule design and fleet assignment model (ISD-FAM) has been developed as a continuation on the work on IFAM from *Barnhart et al.*. In the model the flight leg selection process and aircraft type assignment is executed simultaneously. The presented methodology includes a made distinction between mandatory and optional flight legs and optimizes by eliminating selected optional flights legs. Similar to the earlier work of *Barnhart et al.*, the spill cost and recapture feature is implemented.	[66, 69]
Sherali et al.	2013	An integrated schedule design and fleet assignment model (SDFAM) with itinerary-based demands, flight time flexibility, schedule balance consideration, multiple fare-classes and recapture possibilities.	[70]
Safak	2017	An extension on the fleet assignment model considering fuel burn considerations and carbon emission costs by applying flexibility in cruise velocity to ensure improved passenger demand and connections.	[71]
Wei et al.	2020	A integrated multi-phase flight scheduling and fleet assignment MILP incorporating passenger choice. The passenger choice influence is integrated by means of an attractiveness factor based on itinerary and fare class for a passenger type	[72]
Justin et al.	2022	A hybrid half-leg half-itinerary MILP with a multi-objective approach has been used for tackling a trade-off between maximizing profit and minimizing emission impact. In this approach the optimization of the following four aspects is integrated: flight schedule design, flight frequency, aircraft assignment to flights and passenger itineraries.	[12]

5
Integration of Disciplines

Significant research has been conducted on the development of airline flight scheduling and fleet assignment integration models, as briefly reviewed in chapter 4. This chapter focused mainly on the extension of basic models in the airline planning of conventional aircraft. Recently, research is conducted into the integration of airline planning of electrified aircraft with climate optimization, aircraft design and recharging considerations.

A selection of this past literature on the integration of disciplines into airline planning is reviewed in this chapter, which presents a clear overview of the current development in this field. The chapter starts in section 5.1 with a general introduction to the relevant disciplines that are coupled with airline planning, accompanied by schematic visualization. Then, section 5.2 through 5.4 present an overview of performed research in the integration of disciplines, highlighting key aspects and methods. This chapter concludes with a summarized table that categorizes reviewed research, according to their integrated disciplines.

5.1 General Overview of Discipline Integration

Currently, the research conducted into the integration of additional disciplines in airline planning of electrified aircraft can be split up in three main disciplines. The detailed information about the integration of the most important disciplines is outlined below and a schematic representation is depicted in Figure 5.1.

- **Climate:** The incorporation of aircraft emissions into the airline planning process, focusing on reducing environmental impact on both ground and air operations. This discipline incorporates emissions as either a co-objective in optimization models or as penalizing functions that influence decision-making. More detailed information with corresponding past literature can be found in section 5.2.
- **Aircraft Design:** The coupling between aircraft design and airline planning performs a trade-off for the best electrified aircraft design aligning airline planning objectives. By analyzing the performance of the current aircraft designs and airline's fleet composition, airlines can implement re-designs to achieve improved objectives, such as increasing profit and enhanced operational efficiency. More detailed information with corresponding past literature can be found in section 5.3.
- **Recharging:** The integration of battery recharging for electrified aircraft into the airline planning process is an critical consideration, unlike for conventional aircraft or fleet. The integration of recharging primarily impacts two key performance indicators: TAT and aircraft flight ranges. Several strategies have been proposed to address recharging solutions, including restricting to full charging scenarios and battery swapping solutions. More detailed information with corresponding past literature can be found in section 5.4.
- **Aircraft Design and Climate:** The integration of both aircraft design and climate optimization into airline planning aims at re-designing aircraft and re-composition of an airline fleet, while balancing airline key performance indicators with aircraft emission objectives. This approach combines considerations from both the coupling of climate aspects and aircraft design into a unified model. More detailed information with corresponding past literature can be found in section 5.5.

The visualization of disciplines in Figure 5.1 highlight additional coupling of disciplines that have not been covered above. The three sets of coupling of disciplines[1] that do not include airline planning, depicted in the outer circle of Figure 5.1, are excluded due to the operational focus of the current research. Additionally,

[1]These disciplines sets are the following: integrated recharging and climate optimization, recharging optimized aircraft design, climate optimized aircraft design.

two discipline sets where three areas are integrated[2], indicated by the purple and green triangular area in Figure 5.1, are also not reviewed due to the limited available literature in these areas.

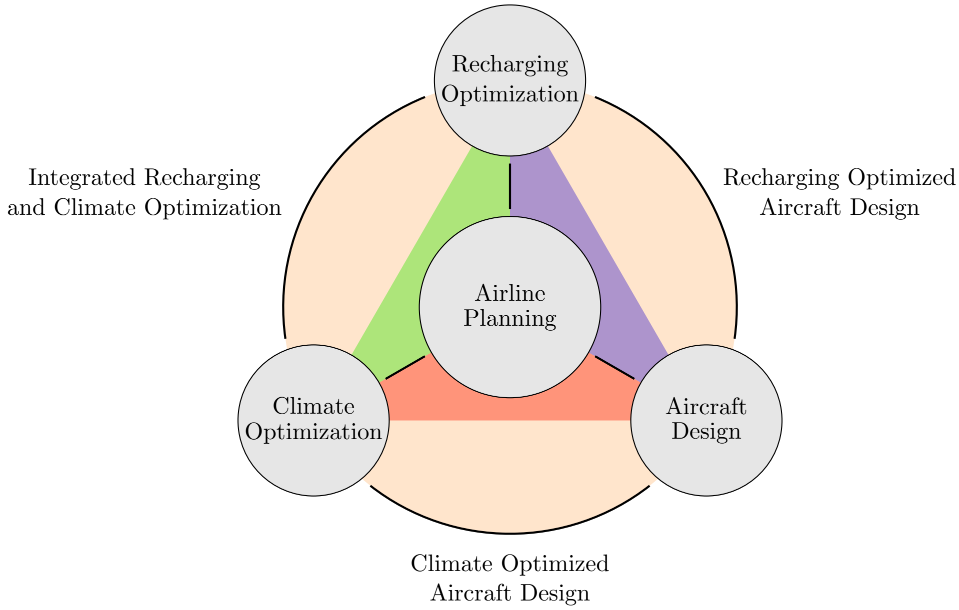


Figure 5.1: Schematic overview representing the integration of airline planning with related disciplines

5.2 Climate Optimized Airline Planning

The integration of climate considerations into flight scheduling and fleet assignment has become a well-researched topic in recent years [12]. Various approaches have been proposed, including the integration of climate objectives as co-objectives, CO_2 penalties and financial tax penalties [12, 15, 26].

A recent study conducted by *Justin et al.* [12] investigated the integration of environmental considerations into electrified flight scheduling and fleet assignment. The study achieved improvements in reducing climate impact, while increasing passengers service. This research is focused on the implementation of all-electric and hybrid-electric flight as a regional air mobility solution in the United States. The research addresses the gap in prior studies that incorporated environmental considerations, but failed to optimize both profitability and environmental impact in flight scheduling, fleet assignment and aircraft routing. The previous attempts of *Safak et al.* [71] and *Ma et al.* [73] introduced integration of emissions into parts of the airline planning process, but did not successfully develop effective strategies for new operations incorporating climate impact reductions. In this work, *Justin et al.* proposed the use of a hybrid half-itinerary half-leg MILP with a hierarchical multi-objective trade-off between financial airline profitability and aircraft emissions. The results of the study indicate that twice the amount of passengers can be fulfilled and carbon emission reductions up to 50 % can be obtained by using electrified aircraft.

This research emphasizes the potential of incorporating environmental impact as a key objective in the flight scheduling and aircraft assignment. Additionally, the approach demonstrates the ability to develop new operational routes in under-utilized current regional networks. Consequently, this research also highlights that additional emission reductions can be achieved through early implementation of carbon emission integration in the flight scheduling and aircraft assignment model. Lastly, the literature emphasizes that several attempts to include climate optimization have been proposed, but very few actually achieve their full potential in balancing profitability and environmental objectives.

[2]These disciplines sets are the following: integration of airline planning, climate optimization and recharging optimization, and the integration of airline planning, aircraft design and recharging optimization.

5.3 Airline Planning Optimized Aircraft Design

The simultaneously optimization for airline planning operations and aircraft design has been extensively investigated by several researchers, primarily for conventional aircraft. However, the recent developments of electrified aircraft requires improved coupling methods for enhanced utilization and climate impact reductions [15].

In 2007, *Taylor and De Weck* [74] developed an initial framework for the simultaneous optimization of aircraft design and network flow, demonstrating it advantages in efficiency and achieving a 10 % cost reduction. This work was continued by a series of studies from *Jansen and Perez*, developing advanced frameworks for integrating aircraft design with airline planning operations [75–79]. This series included integration of these disciplines with additional research into the incorporation of fuel burn minimization [75], uncertain passenger demand [76], and multiple market considerations [77, 78]. These studies emphasize the potential for cost reductions when fleet network allocation is integrated with conventional aircraft design.

In 2019, *Weit et al.* [80] explored the integration of network optimization and hybrid-electric aircraft design. This study incorporated the hybridization ratio as a key design aspect of hybrid-electric aircraft aiming for profit maximization by allowing decreases in payload to extend range. Additionally, the research also investigated the effect of accompanying additional batteries as a replacement of certain payload mass to enhance operational flexibility.

More recently, a series of research into the coupling of aircraft design and airline planning operations have been conducted at Delft University of Technology by *Zuijderwijk*, *Scheers* and *Antunes*. In 2022, *Zuijderwijk* [81] presented an framework connecting strategic airline planning to electrified aircraft design, including insights into fleet electrification strategies for airlines. In 2023, *Scheers* [15] built upon this by developing a framework for climate optimized hybrid-electric aircraft design integrated with strategic airline planning. Lastly, in 2024 *Antunes* [26] further developed this framework by incorporating the effects of operating hybrid-electric aircraft outside their on-design conditions.

5.4 Recharging Optimization Integrated Airline Planning

The integration of battery recharging is considered one of the most significant challenges for making electrified aircraft a viable alternative to conventional aviation [10]. The reason stems from the impact of battery recharging duration on the TAT, resulting in electrified flight being economically impractical. The integration of recharging into the flight scheduling and fleet assignment is crucial in the development of electrified airline networks. However, there is limited research into the modeling of flight scheduling and fleet assignment with integrated recharging optimization. Many studies on electrified flight scheduling, fleet assignment and aircraft routing assume instant recharging, battery swapping possibilities or neglect recharging completely [12, 80, 82–84]. However, two recent studies propose alternative approaches to address these challenges.

In 2020, *Mitici & Pereira* [83] approached the scheduling of all-electric aircraft by allowing aircraft to either recharge or swap their batteries. The study includes a two-phase optimization model including planning and recharging aspects. The first phase develops a flight and battery recharging schedule, while simultaneous determining the required fleet size of electric aircraft. Then, the second phase optimizes for charging times aiming at a minimization of charging stations and batteries. The model integrates recharging into scheduling by addressing the following three factors:

- **Residual SoC:** The SoC of the battery after depletion from the previous flights.
- **Charging characteristics:** The evolution of SoC over time, based on the charging profile and the current SoC.
- **Required SoC:** The required SoC for completing the next flight.

In this study, the battery recharging profile is defined as a bi-linear curve, consisting of a fast charging phase and slow charge phase from 0 % - 90 % and 90 % - 100 %, respectively.

In 2023, *Vehlhaber & Salazar* [82] proposed a model that integrates battery recharging with all-electric aircraft fleet assignment and routing, focusing on optimizing for sustainable energy resources. Unlike most of earlier conducted research, this study integrates the SoC into the fleet assignment model based on passenger demand over flight legs. Additionally, the developed method models the SoC over time as either discharging (in-flight state) or recharging (ground state), and includes energy calculations for electric aircraft flight performance. The combination of these features translates into a set of equations able to optimal model the SoC over time, adhering to charging power constraints and flight requirements.

These two studies approach the modeling of the SoC as a time-series of all-electric aircraft as part of a larger objective. The former study includes optimization for required energy levels in order to fulfill the next mission. The latter divides the time series by either recharging and discharging and integrates this with closely with fleet assignment and routing decisions. These approaches emphasize the advancements in integrating battery recharging into airline planning for all-electric aircraft.

5.5 Climate Optimized Aircraft Design and Airline Planning

The integration of airline planning with climate optimization and aircraft design has recently come to more attention among researchers due to its potential to tackle both operational efficiency and environmental considerations.

A recent study by *Hoogreef et al.* [16] demonstrated that the integration of these three disciplines can result in significant emission reductions at the cost of small decreases in profitability. The methodology was applied to a regional network case, resulting in emission reductions of 11 % at the cost of a 13 % decrease in profitability compared to a conventional kerosene fleet. The study utilized an iterative process that coupled fleet and network allocation with aircraft, incorporating an evaluation of the off-design conditions before applying a climate optimization module. The model proposes new aircraft designs based a clustering of the payload-range diagram with corresponding design categories including payload, range and runway distance.

The research illustrates the effect of integrated aircraft design on profitability and carbon emission reductions. The findings emphasize the potential of integrating these disciplines to develop more sustainable aviation operations.

5.6 Concluding Remarks of Integration of Disciplines

A schematic overview of reviewed literature has been developed, summarizing the dedicated integration of disciplines by check marks. This overview is presented in Table 5.1 on the following page, providing a clear overview of the current available research on the integration of discussed disciplines. From the previous discussed literature and Table 5.1, it is evident that limited research has been conducted into the integration of recharging optimization into flight scheduling and aircraft routing. Furthermore, the table highlights that no research has been conducted into the integration airline planning with all three other discussed disciplines. This highlights the need for further research into the integration of these disciplines.

Table 5.1: Overview of research on the development of integrated electrified aircraft models

Authors	**Year**	**Airline Planning**	**Aircraft Design**	**Climate Optimization**	**Recharging Optimization**	**Reference**
Taylor & De Weck	2007	✓	✓			[74]
Weit et al.	2019	✓	✓			[80]
Roy et al.	2017	✓	✓			[85]
Mitici & Pereira	2020	✓			✓	[83, 86]
Zuijderwijk	2020	✓	✓			[81]
Justin et al.	2022	✓		✓		[12]
Oosterom & Mitici	2023				✓	[84]
Vehlhaber & Salazar	2023	✓		✓	✓	[82]
Hoogreef & Scheers	2023	✓	✓	✓		[15, 16]
Chan et al.	2023	✓				[10]
Antunes	2024	✓	✓	✓		[26]

6
Conclusions and Research Proposal

This chapter provides the conclusions derived from the reviewed literature in section 6.1. Consequently, it presents the research gap and research question with corresponding sub-questions in section 6.2 and 6.3, respectively. The chapter closes of with the formulation of the research objective in section 6.4.

6.1 Conclusions

The main conclusions derived from the analysis of the previous chapters has been summarized in this section. This section first presents the most important findings from the retrieved information on the background on aircraft electrification. Then, it provides the most relevant aspects of airline planning operations. Lastly, the research on the integration of disciplines is summarized.

Background on Aircraft Electrification

The electrification of aircraft is primarily driven by cost reduction and significant emission reductions, with a particular focus on addressing solutions to the regional travel market. This electrification of aircraft have resulted in the development of three main type of aircraft: all-electric aircraft, hybrid-electric propulsion aircraft and turboelectric aircraft. These aircraft can be categorized using the developed relationship for degree of hybridization, which quantifies the proportion of electrically driven power and energy relative to the total power and energy. The degree of hybridization plays an critical role in the mission profile optimization, allowing for optimal usage of battery energy across various flight phases. Another key consideration is the in-flight energy management, which provides flexibility in constraining the final state of charge of the battery and enables optimal energy usage of energy throughout the flight. A key aspect of battery recharging in electric flight is efficient and fast recharging to overcome limitation in turn-around time. The literature presented two alternative solutions to conventional (CC-CV) charging: boost-charging (CV-CCCV) and multi-stage CC (MCC) charging. These alternatives provide advantages in efficiency and increases in charging speeds up to 22.5 %. An overview was of CO_2 emissions was presented for electrified aircraft, considering both kerosene and battery as fuel source.

Airline Planning Operations

The airline planning process consist of three main phases: fleet planning, route planning and schedule development. Flight scheduling and aircraft assignment represent the most critical components. This phase integrates the development of a flight schedule by selecting flight legs to be operated and the assignment of aircraft in which specific aircraft need to be assigned to this schedule while adhering to key constraints: cover, balance and availability. Another key consideration is the development of a space-time network, allowing for the balance constraints of aircraft. Numerous variations to the flight scheduling and aircraft assignment model have been developed, incorporating advanced features such as demand optimization, spill cost minimization and recapture, and re-timing of flights. Two primary mathematical techniques for solving these optimization problems have been proposed: mixed-integer linear programming and dynamic programming. Mixed-integer linear programming proposes advantages over dynamic programming for large-scale linear models with binary, integer, and continuous variables. Conversely, dynamic programming is more suitable for non-linear, state-dependent problems that can be divided in smaller sub-problems, enabling the incorporation of state-specific decisions at each stage of the optimization process. Both techniques are essential for advancing airline planning operations and should be selected based on their suitability and applicability to the specific problem.

Integration of Disciplines

Recently, much research has been conducted into the integration of airline planning with other disciplines such as climate optimization, recharging optimization and aircraft design. The reviewed literature focuses on these three disciplines individually, while considering also the integration of a combination of two of these disciplines with airline planning: climate optimization and aircraft design. The integration of climate considerations is often achieved by including climate based performance indicators in the objective function or the addition of a penalty function. Then, aircraft design can be integrated by using an iterative approach in which aircraft design is optimized for the limitations of the given network, derived from initial airline planning. The integration of (partial) battery recharging is vital for the development of electrified aviation, but is currently lacking advanced models. The integration of both climate and aircraft design have recently been researched by incorporating key flight performance indicators. The collection of literature in the field of integration of disciplines, focused on coupling with airline planning, brings the underdevelopment of recharging under attention. Finally, this collection of literature also highlights that no combined integration of all aforementioned disciplines is yet researched.

6.2 Research Gap

The research gap identified from the aforementioned conclusions is formulated as follows:

> *The integration of partial recharging strategies with flight scheduling and aircraft assignment, while simultaneously considering airline profitability, climate impact, and electrified aircraft design.*

6.3 Research Question

The research question derived from the described research gap, to be addressed during this thesis, is formulated as follows:

> *What is the effect of incorporating partial recharging strategies into flight scheduling and aircraft assignment on airline network profitability, carbon emission reduction, and the design of electrified aircraft?*

This research question is divided into smaller sub-questions, each designed to contribute to addressing the main research question. These sub-questions are stated as follows:

1. Which optimization solver, Mixed-Integer Linear Programming or Dynamic Programming, is most suitable for integrating (partial) recharging into flight scheduling and aircraft assignment models, considering the nonlinearity and computational complexity?
2. How can battery recharging strategies be effectively incorporated into flight scheduling and aircraft assignment?
3. What trade-offs exist between airline profit maximization and carbon emission minimization?
4. What electrified aircraft design parameters require to be adjusted to improve network performance and how can these be adjusted to achieve the desired operational and environmental targets?
5. How do different battery charging profiles and strategies affect airline network performance in terms of profitability and environmental impact?
6. What is the impact of advancements in battery gravimetric energy density on airline profitability and environmental impact?

This research aims at supporting the research question by means of a comparative case study addressing the question as stated below:

> *How does the performance of airline networks with partial recharging compare to those limited to full recharging or to conventional aircraft in terms of airline profitability and carbon emission reduction?*

6.4 Research Objective

The research objective is constructed based on the research question and its sub-questions from section 6.3 and is stated as follows:

> *This research aims to analyze the impact of partial recharging strategies on airline network performance by optimizing the integration of flight scheduling and aircraft assignment with recharging strategies and electrified aircraft design, while maximizing profitability, reducing carbon emissions and adhering to electrified aircraft constraints.*

7 Research Approach

This chapter presents a preliminary planning consisting of five main phases for the proposed research in chapter 6, which is schematically represented by Figure 7.1. These phases are in more detail described in section 7.1 - 7.5.

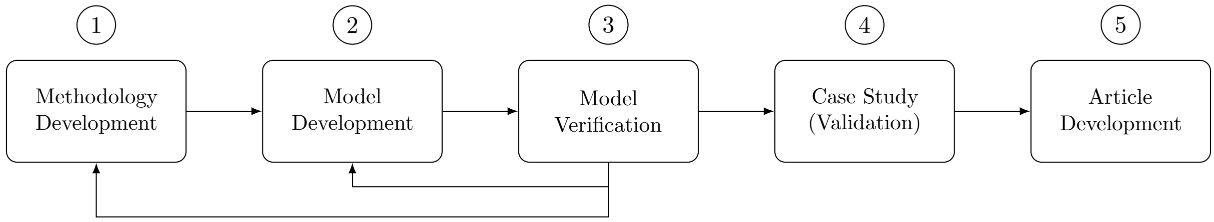


Figure 7.1: Schematic overview of the five main phases of the research approach

7.1 Methodology Development

The first phase after the literature study and the research proposal will consist of the methodology development. During this phase, a methodology will be developed to provide the tools to answer the research question. The methodology will consist of four sub-modules that are inter-connected and these will be integrated in a later stage. These sub-modules are as follows:

- Development of the flight scheduling and aircraft assignment model.
- Integration of climate optimization.
- Integration of partial recharging strategies.
- Integration of electrified aircraft design.

Development of the Flight Scheduling and Aircraft Assignment Model
This module focuses on developing a dedicated flight scheduling and aircraft assignment model. Several critical aspects must be considered during development, including selection of a suitable mathematical solver, formulation of the objective function, and the identification of constraints. Furthermore, external data requirements need to be considered, in which the types of input data and reliable resources are evaluated.

Integration of Climate Optimization
This module focuses on the integration of carbon emissions reduction as part of the objective function. The challenge is in the evaluation of the trade-offs required to be performed in the development of a multi-objective objective function. Furthermore, the modeling of used electricity and burned fuel with corresponding emissions indices for flights must be developed and integrated.

Integration of Partial Recharging Strategies
This module focuses on the integration of partial recharging strategies as part of the flight scheduling and aircraft assignment model. The different implementation options and modeling techniques of battery recharging strategies as a function of time need to evaluated and the most effective method needs to be integrated.

Integration of Climate Optimization
This module focuses on the integration of electrified aircraft design aspects. The primary objective is to select the most appropriate coupling technique for optimized electrified aircraft design. A trade-off must be performed between several factors such feasibility and ability for implementation to ensure the coupling strategy is effective and practical.

7.2 Model Development

The model development phase focuses on the transforming the theoretical methodology into an efficient, well-structured computational model. The following key aspects are essential to this phase:

- **Python Environment:** The creation of a well-structure Python project with good package management, input and output setup, and version control for tracking changes.
- **Computational Model:** The translation of the theoretical methodology to structured code, including optimization solvers, sub-module integration and additional features.
- **Documentation:** The appropriate documentation of the computational model using code documentation, a user guide and proper connection to the theoretical background.

7.3 Model Verification

The developed Python model must undergo a verification process to ensure it performs as intended and produces reliable results. The verification will consist of several phases to be carried out and is outlined below:

- **Model Verification Part I:** This phase focuses on verifying the developed model up to the mid-term review. The goal is to ensure that the results and findings presented during this review are of high fidelity and accuracy. The scope of this verification will depend on the progress of the model and methodology.
- **Model Verification Part II:** This phase extends the verification process to the entire model as a continuation of Part I. In case of adjustments to earlier developed components, re-verification must be applied to ensure reliability of the entire model.
- **Sensitivity Analysis:** This phase evaluates the level of robustness of the model by analyzing the influence of variations in input parameters on output results. The input variables will be varied with realistic range values and the corresponding impact on the results will be analyzed accordingly.

The model verification for Part I and Part II include the following two components:

- **Data Verification:** This step is aimed at ensuring that input data is accurate, complete and consistent. Several verification steps will include checks for confirmation of alignment of data with intended model requirements.
- **Computational Verification:** This step is aimed at ensuring that the optimization model functions as designed. Main elements such as functions, classes and modules will be tested to confirm correctness using known inputs and expected outputs. This process ensures that the computational model corresponds to the theoretical methodology.

7.4 Case Study

A case study will be developed to address two aspects: the validation of the model and the execution of a comparative analysis to answer the research question.

First, the case study allows the developed methodology and corresponding computational model to be validated against real-world data and scenarios. The main objective is to assess the reliability, applicability and performance of the model. Another important part of the validation process is the research into a suitable real-world scenario providing representative data and allows for accurate validation.

Secondly, the case study will serve as a means to conduct a comparative study. A comparative analysis can will be executed by changing only the electrified aircraft dependent data, while keeping the data environment unchanged. This allows the comparative analysis to be only dependent on the the modeling and therefore no unrelated factors will influence the outcome of the study.

7.5 Article Development

The last phase of the research is the development of the article, in which all the performed research need to be concisely presented. The article will consist of the elements listed below:

1. **Abstract:** A brief summary including all aspects of the article.
2. **Introduction:** A short introduction into the relevance of the research topics and a review of past literature vital for the remainder of the article.
3. **Methodology:** A description of the final methodology used for answering the research question.
4. **Case Study:** The validation of the model and comparative analysis by means of the case study.
5. **Results & Discussion:** The presentation of the results with corresponding discussion.
6. **Conclusion & Future Recommendation:** The conclusions that are derived from the performed research and the recommendation for future research.

8

Research Planning

This chapter provides an overview of the initial made planning for the entire research duration, including the literature review and research proposal that have already been conducted. The research phases haven been summarized in Table 8.1 and an overview of the milestones, as discussed during the kick-off of this research, are presented in Table 8.2.

Table 8.1: Planning of research phases

Week	**Phase**	**Description**
1 – 6	Literature Review & Research Proposal	The development of a research proposal by defining the research gap based on past articles, theses and other forms of literature.
7 – 12	Methodology Development	The development of the methodology as proposed in the research proposal based on literature and knowledge. The methodology can be split up over several phases: 1. Development of the flight scheduling and aircraft assignment model. 2. Integration of climate optimization. 3. Integration of partial recharging strategies. 4. Integration of electrified aircraft design. 5. Integration of all inter-connected sub-modules.
10 – 15	Model Development	The translation of the developed theoretical methodology into an efficient, well-structured computational model.
12 – 15	Model Verification Part I	The verification of the first part of the developed model, up until the mid-term review.
12 – 15	Case Study Setup	Development of the case study for validation and comparative analysis.
15 – 20	Iteration process	The improvement of the model through iterations and feedback from initial results and further development of Case Study.
15 – 20	Case Study	The application of the model on the developed case study, with corresponding adjustments.
18 – 20	Model Verification Part II	The verification of the second part of the developed model and the potential re-verification of the adjusted model.
20 – 25	Reporting	The development of the technical article, including all relevant components.
25 – 32	Thesis Defense Preparation	The submission of all required documents and preparation for the research defense presentation.

Table 8.2: Research milestones with corresponding dates

Week	Milestone	Date
1	Starting Date	14-11-2024
2	Kick-off	22-11-2024
6	Research Proposal Deliverable	20-12-2024
8	Research Proposal Review	07-01-2025
15	Midterm Deliverable	07-03-2025
16	Midterm Review	14-03-2025
25	Final Draft	16-05-2025
27	Green Light Review	30-05-2025
28	Request Examination	02-06-2025
30	Research Portfolio Submission	13-06-2025
32	Thesis Defense	30-06-2025

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