

Optimizing the battery charging and swapping infrastructure for electric short-haul aircraft—The case of electric flight in Norway

Simon van Oosterom ^{a,*}, Mihaela Mitici ^b

^a Faculty of Aerospace Engineering, Delft University of Technology, Kluyverweg 1, HS 2926 Delft, The Netherlands

^b Faculty of Science, Utrecht University, Heidelberglaan 8, 3584 CS Utrecht, The Netherlands

ARTICLE INFO

Keywords:

Electric aviation
Battery swapping systems
Commuter air transport
Scheduling
Infrastructure sizing

ABSTRACT

Recent advances in battery technology have opened the possibility for short-haul electric flight. This is particularly attractive for commuter airlines that operate in remote regions such as archipelagos or Nordic fjords where the geography impedes other means of transportation. In this paper we address the question of how to optimize the charging infrastructure (charging power, spare batteries) for an airline when considering a battery swapping system. Our analysis considers the expenditures needed for (i) the significant charging power requirements, (ii) spare aircraft batteries, (iii) the used electricity, and (iv) delay costs, should the infrastructure not be sufficient to accommodate the flight schedule. The main result of this paper is the formulation of this problem as a two-phase recourse model. This is required to account for the variation of the flight schedule throughout a year of operations. With this, both the strategic (infrastructure sizing) and tactical (battery recharge scheduling) planning are addressed. The model is applied for Widerøe Airlines, with a network of 7 hub airports and 36 regional airports in Norway. The results show that a total investment of 4412 kW in electricity power supply and 25 spare batteries is needed for the considered network, resulting in a daily investment of €11700. We also quantify the benefits of considering an entire year of operations for our analysis, instead of just one congested day (7% cost reduction) or one average day of operations (31% reduction) at the most congested airport.

1. Introduction

To limit anthropogenic emissions, the aviation industry targets climate-neutrality by 2050 (UNFCCC, 2021). Opposed to the automotive sector, where electric vehicles are now fully rolled out across the globe by major manufacturers and hold a 10% share of total sales worldwide (Paoli et al., 2022) with up to 80% in Norway (Klesty, 2022), the low energy density of batteries has prevented a similar transition in the aviation sector. Emission reductions in aviation have for now been focused on e.g. improving operations by electric taxiing (Soltani et al., 2020; Guo et al., 2014) or electric urban air mobility (Garrow et al., 2021; Shao et al., 2021). Nevertheless, battery technologies have greatly developed over the last ten years: gravimetric energy density has almost tripled (Balogun et al., 2018), volumetric energy density has increased eightfold (Muralidharan et al., 2022) and prices per kWh have decreased tenfold (Ziegler and Trancik, 2021). As such, battery technology is now at the level where it can be used for small electric aircraft (Holland, 2021; Taraldsen, 2021; Taylor-Marriott, 2022).

Electric aircraft (e-AC) are becoming an alternative for high frequency commuter airlines operating short-haul flights in remote areas with low passenger volumes (Justin et al., 2022). By using electric motors, which use less expensive energy and require less

* Corresponding author.

E-mail address: s.j.m.vanoosterom@tudelft.nl (S. van Oosterom).

maintenance, these aircraft are cleaner and cheaper to operate than their kerosene-fueled equivalents. This would improve access to remote regions such as archipelagos, deltas and fjords, where the geography and low population density cannot justify an extensive road/train network.

From an operational point of view, however, replacing conventional aircraft with e-AC poses challenges. Batteries have to be recharged quickly in order to maintain short turnaround times. However, charging only during the turnaround of an aircraft results in a capricious energy demand with high peaks. To sustain this, an overly large and expensive charging infrastructure may be needed (Brdnik et al., 2022).

A way to circumvent these operational problems is to consider swapping batteries between flights. For this, we aim to determine the charging infrastructure (how many spare batteries are needed) and the charging schedule for these batteries. The objective of this paper is to determine an optimal charging infrastructure while accounting for the variability of the operations over a large period of time. This is achieved by means of a recourse model that optimizes the infrastructure which considers an entire year of operations. This is in contrast to existing studies, which limit their optimization models to a single day of operations, such as a peak or average day of operations.

The recourse model has a hierarchical structure. It consists of one mixed-integer linear program as master problem and a second mixed-integer linear program as subroutine. The master problem determines an optimal total charging power and number of spare batteries at each airport (sizing the charging infrastructure). The objective is to minimize the infrastructure acquisition cost and the operational cost (cost of electricity and potential flight delays). To capture the seasonality of the air traffic, flight schedules from an entire year of operations are considered. In the subroutine, a schedule for battery swapping and charging is determined for one day of operations, given a charging infrastructure. We apply our model for Norwegian carrier Widerøe Airlines and its network of regional and hub airports. Widerøe, Scandinavia's largest regional airline, aims to introduce a fully electric aircraft to the market by 2026 (Taraldsen, 2021). We consider an e-AC with the specifications of the already existing Eviation Alice aircraft. The results show that a total charging power of 4400 kW and 23 spare batteries are required, leading to a daily cost of €11,600. We also quantify the benefit of optimizing the infrastructure over an entire year of operations, instead of optimizing for only a peak traffic day or a median traffic day.

The main contributions of this paper are:

- We propose a recourse model that determines an optimal battery charging infrastructure for a network of airports, assuming a battery swap system. This recourse model is necessary to account for the variability of the flight schedule throughout the year when optimizing the charging infrastructure. This is in contrast to existing studies, which optimize the infrastructure considering a single (representative or peak) day of operations.
- Our proposed model minimizes the sum of the infrastructure acquisition costs (charging capacity and spare batteries), and the operational costs (electricity costs and flight delays due to battery charging).
- We illustrate our model for a network of 7 hub and 36 regional airports in Norway, using an existing flight schedule from a year of operations. We also consider an already existing configuration of an electric aircraft (Eviation Alice) designed for short-range flights.

The remainder of the paper is structured as follows. In Section 2, we discuss literature on scheduling operations at- and sizing of-battery swapping stations, as well as e-AC charging infrastructure. In Section 3, we describe the problem of e-AC charging infrastructure management. In Section 4, the recourse model for e-AC charging infrastructure management is introduced. In Section 5, we illustrate the performance and results of our model in a case study for a regional carrier operating electric aircraft in Norway. In Section 6 we quantify the advantage gained by our recourse model which accounts for an entire year of operations, versus an optimization model which considers only a single day (peak-traffic or median-traffic day). Concluding remarks and future research directions are given in Section 7.

2. Prior work and contributions

The concept of battery swaps systems (BSSs) as an alternative to plug-in charging has been proposed as a means of reducing recharge times, to protect the electricity grid against high and unpredictable demand, and to limit battery degradation (Sarker et al., 2015; Sultana et al., 2018). BSSs have mainly been studied in the context of electric cars, electrified public transport busses and delivery drones (see e.g. Schneider et al. (2018), Ayad et al. (2021), and Kwizera and Nurre (2018)). Two research themes regarding BSSs are relevant for this study: the sizing of the BSS infrastructure, and the scheduling of charging of the batteries.

In the past years, several studies have addressed the operations' scheduling of BSSs, which considers determining when to recharge the batteries at the BSS to ensure a sufficient stock. Worley and Klabjan (2011) propose a model to optimize the charging schedule at a BSS for day-ahead planning, while considering a fixed and predetermined demand for full batteries. They formulate the problem as a mixed-integer linear program with the objective of maximizing the revenue by supplying full batteries to customers while minimizing the electricity costs. This model is expanded by Nurre et al. (2014), who add Vehicle-to-grid (V2G) charging as a possibility for increasing BSS revenue, and by Park et al. (2017), who study the minimization of waiting time for charged batteries. All of these studies, however, assumed a known demand for batteries before optimization. Sarker et al. (2015) were the first to recognize the uncertainty in the demand of a BSS, proposing a robust optimization approach to ensure a sufficient supply of fully charged batteries. However, this study was limited to using fixed charging times, as opposed to a state-of-charge dependent one. Additional studies have focused on minimizing battery degradation (Wu et al., 2017; Asadi and Nurre Pinkley, 2021; Kwizera and Nurre, 2018). In this paper, we assume that the flight schedule is known and consider deterministic planning like Worley

and Klabjan (2011) and Park et al. (2017). We expand upon the previous work done by considering partial charging, and our objective also considers the minimization of the waiting time for a full battery, apart from the electricity costs. Inextricably linked with the optimization of the battery recharge schedule is the problem of recharge infrastructure sizing: determining how many batteries can be charged simultaneously and how many spare batteries to keep in stock at the station. Worley and Klabjan (2011) combine a day-ahead scheduling of a BSS with determining the required spare battery inventory. However, batteries cannot always be acquired a single day ahead, and are hence not a flexible asset. As such, there is a trade-off between making long-term investments in infrastructure (spare batteries and chargers), and short-term operational expenses related to the charging schedule (electricity costs, battery degradation, etc.). This is the reason why the two problems are not solved simultaneously in more recent studies. This two-phase approach to the problem was first proposed by Schneider et al. (2018), who minimize the sum of the investment costs for batteries and chargers and the costs of operating the BSS (customers served against electricity cost). Customer arrival times are assumed to be exponentially distributed. Using a Monte-Carlo Dynamic Programming approach, a near-optimal policy for charge scheduling was developed. Sun et al. (2018) consider a similar problem, but add a minimum level-of-service for the customers, while only considering fixed charging times. Later, Sun et al. (2019) expand the problem to a three-phase approach where the number of required chargers and batteries is determined in two phases. Other studies focus on combining the sizing of BSSs with finding an optimal location (see Mak et al. (2013) or Liu et al. (2016)) or simultaneously routing the vehicles which use the BSS (see Ayad et al. (2021)). For an extensive literature overview of optimization models for BSSs, we refer to Zhan et al. (2022). In this study, we consider a two-phase approach (sizing the charging capacity and spare batteries in the first phase, scheduling the recharging operations in the second), similar to Schneider et al. (2018), Sun et al. (2018). We extend these approaches in by considering a state-of-charge dependent time of charge for the batteries. We also allow for preemptive battery charging during the second phase.

There are a number of studies where optimization of battery charging operations is performed in the context of electric aircraft (e-AC). Justin et al. (2020) consider the minimization of the required investment costs of the infrastructure (chargers and spare batteries) in order to support a BSS for small e-AC. In their analysis, flight schedules and battery recharge times are assumed to be known beforehand. They apply their models for Mukuele Airlines (Hawaii) and Cape Air (New England). Salucci et al. (2019) perform a similar study, considering variable electricity prices throughout the day, but assume identical flight duration and battery recharge times (similar to Nurre et al. (2014)). This work was further expanded by Trainelli et al. (2021), who also considers the procurement and routing of a fleet of e-AC from a hub airport. They minimize the sum of the acquisition costs of the electric aircraft, charging points and spare batteries, and the electricity costs. A similar problem is studied by Mitici et al. (2022), where a fixed electricity price is assumed. A hierarchical cost function is assumed to solve the problem more efficiently (first for aircraft fleet sizing and routing, then for charging infrastructure sizing and scheduling). Guo et al. (2020) also consider the availability of electricity based on renewable energy sources. Finally, the sizing of aircraft charging infrastructure at the gates/apron has been studied by Doctor et al. (2022).

None of these studies have separated the infrastructure sizing (number of aircraft, chargers, spare batteries) from the scheduling of operations. As such, these solutions are optimized for one day of operations, instead of for the (predicted) traffic throughout the entire year. A two-phase approach, such as in Schneider et al. (2018) or Sun et al. (2018), which takes demand seasonality into account has been shown to outperform such a single-phase approach. We introduce a tactical-phase battery recharge scheduling model, an extension of the work of Justin et al. (2020). But opposed to the previous literature on charging infrastructure for electric aircraft, we assume that the infrastructure size is predetermined and cannot be optimized simultaneously. For this, we introduce an infrastructure sizing model which accounts for demand variation throughout the year. This inclusion is the main contribution of our paper.

3. Problem description

Electric aircraft operations with battery swapping

We consider an airline operating a fleet of short-haul electric aircraft, each equipped with one battery. Let R and H denote the set of regional and hub airports, respectively, where these electric aircraft fly between. Aircraft can recharge their batteries at all airports during turnaround, but this is too short to fully recharge it. In order to quickly replenish the battery, the aircraft can swap it for a fully charged one during turnaround. We assume that only the hub airports have the infrastructure needed to swap the batteries of the electric aircraft. We also assume that a battery is swapped with a new, fully-charged battery every time an aircraft visits a hub airport. Fig. 1 shows an example of operations of one electric aircraft. At the start of the day, the aircraft flies from hub H1 to H2 via regional airports R1 and R2. At R2, the battery is partially recharged. This aircraft swaps its battery at H2. From H2, the aircraft flies to H3, where it swaps its battery again.

Electric aircraft flight schedules

Let D denote a set of days of an entire year during which the airline operates. A flight schedule for day $d \in D$ consists of a list of arrival and departure times for an entire day of operations. Let T_d denote the time interval during one day when the aircraft fly to and from a set of airports (hubs and regional airports). Let F_{arr}^{dh} and F_{dep}^{dh} denote the set of flights operated by electric aircraft that arrive and depart at hub airport $h \in H$ on day $d \in D$, respectively. Let $\tau_f^{arr} \in T_d$ denote the arrival time of flight $f \in F_{arr}^{dh}$ and let $\tau_f^{dep} \in T_d$ denote the departure time of flight $f \in F_{dep}^{dh}$.

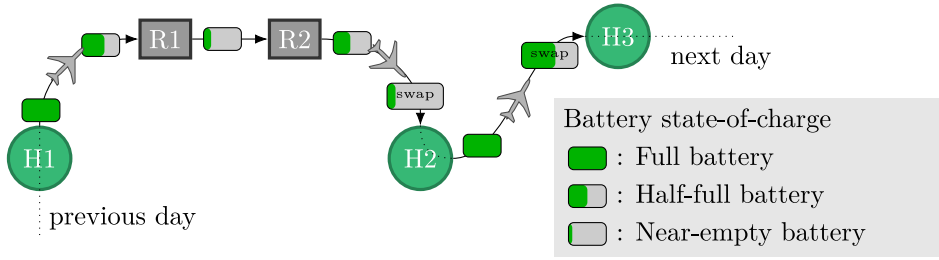


Fig. 1. Example of a day of operations for an electric aircraft.

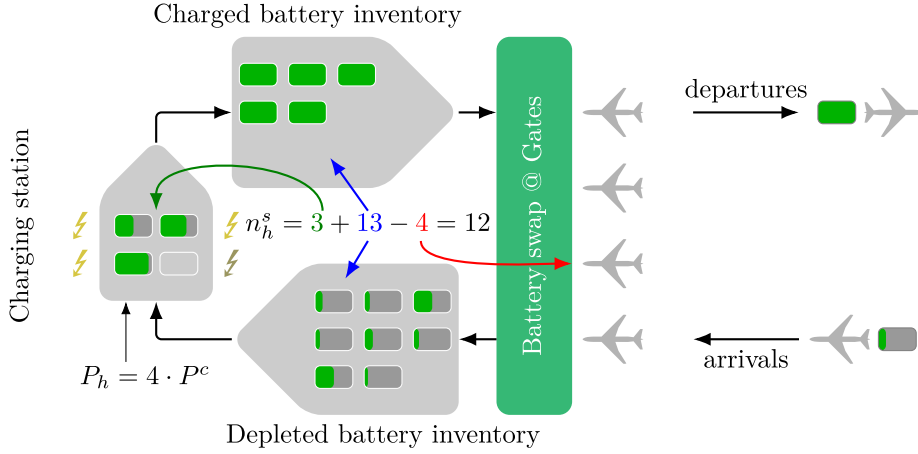


Fig. 2. Overview of the battery swapping and recharging process at an airport. The battery charging capacity at the airport is $P_h = 4 \cdot P^c$ (at most four batteries can be charged at max power), and there are 12 spare batteries (three currently being charged, 13 waiting at the depot, minus four which should depart on the four parked aircraft).

Battery swaps

We assume that each hub airport is equipped with one charging station. Upon arrival at a hub airport, the used battery of an electric aircraft is swapped with a new fully charged battery. Let B_{arr}^{dh} denote the set of batteries which arrive with flights F_{arr}^{dh} . For each flight $f \in F_{arr}^{dh}$, let $b_f \in B_{arr}^{dh}$ be the battery with which it arrives. Let τ^{lr} denote the time it takes to bring the used battery to the charging station. The same amount of time τ^{lr} is assumed to be required to bring a fully charged battery from the charging station to an aircraft. Thus $\tau_{b_f}^s = \tau_f^{arr} + \tau^{lr}$ is the time the battery $b_f \in B_{arr}^{dh}$ used for flight $f \in F_{arr}^{dh}$ arrives at the charging station. At the charging station, each battery charges at a constant rate P^c until it is fully charged. Let τ_b^c denote the required charging time of battery $b \in B_{arr}^{dh}$. Finally, in order to depart on time, a new battery for flight $f \in F_{dep}^{dh}$ needs to depart from the charging station to the gate at the latest time $\tau_f^e = \tau_f^{dep} - \tau^{lr}$.

Battery charging station

Let P_h denote the charging capacity at hub airport h , i.e., the total power with which batteries can be charged simultaneously at the airport. Let $P_h \cdot c^p \in \mathbb{R}_+$ denote the daily cost to provide this charging power at hub airport h . Let $n_h^s \in \mathbb{N}$ denote the number of spare batteries available at a hub airport h . Let $c^s \in \mathbb{R}_+$ be the daily cost of having one spare battery at a hub airport.

We assume that batteries can be charged preemptively. We also assume that the price of electricity varies throughout the day and is given by a function $c^e : T_d \rightarrow \mathbb{R}_+$ of time.

Fig. 2 shows an example of a hub airport and its charging infrastructure, i.e., with charging power $P_h = 4 \cdot P^c$ and $n_h^s = 12$ batteries available at this airport for swap, out of which 3 batteries are charging and 13 batteries are idle in the inventory, from which there are 4 which have to depart with an aircraft currently parked at the airport. Each aircraft needs to depart from the airport with a fully charged battery.

3.1. Battery charging station sizing

Given a hub airport $h \in H$ and set of flight schedules during days D , the main objective of our study is to determine a suitable battery charging infrastructure size (P_h, n_h^s) . This problem is solved once for each hub airport before the start of D , to allow time

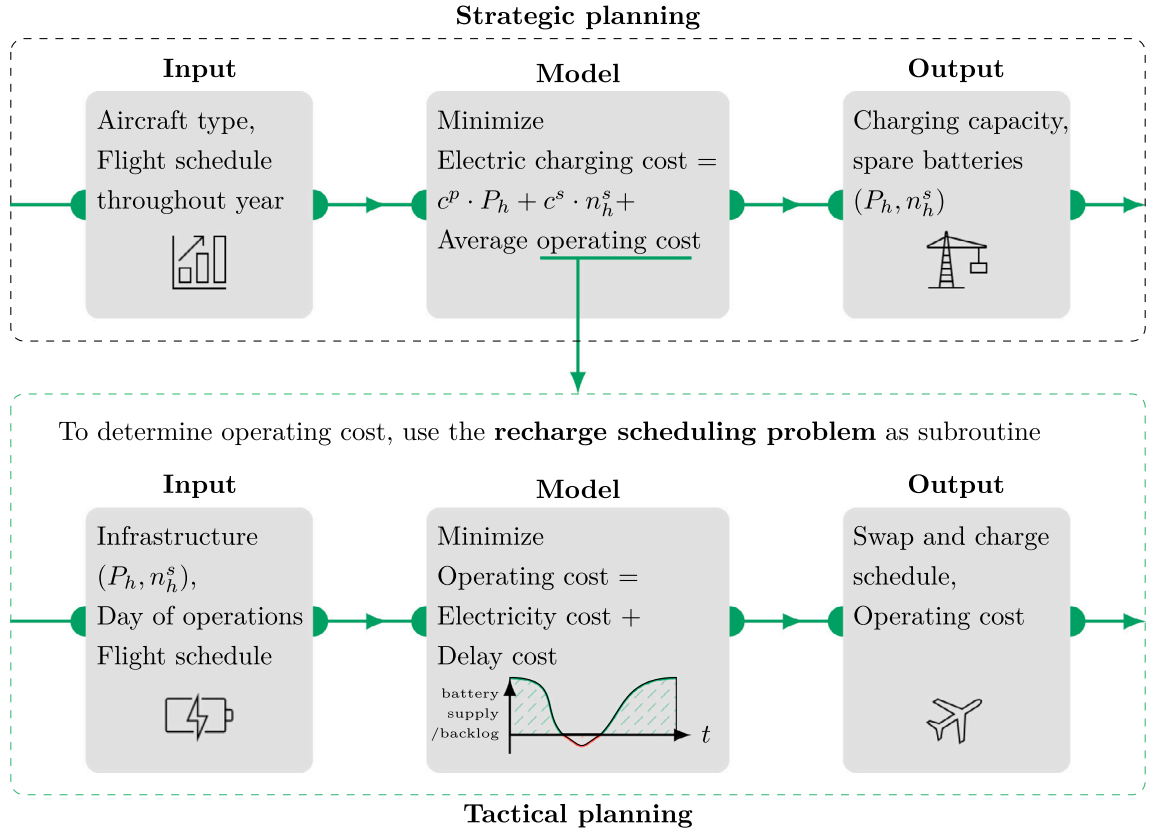


Fig. 3. Recourse model for sizing the charging infrastructure and recharge scheduling for e-AC battery swaps. Sizing the charging infrastructure is a strategic planning problem, whereas creating a recharge schedule is a tactical planning problem.

for charging station construction. The infrastructure is optimized to minimize the sum of the capital expenditures ($P_h \cdot c^p + n_h^s \cdot c^s$) and average charging schedule operating costs over D are as low as possible. The value of the latter for each $d \in D$ is given by the battery recharge schedule optimization (Section 3.2), which is used as a subroutine.

3.2. Swapped aircraft batteries recharge scheduling

Given a certain charging infrastructure size (charging capacity P_h and number of spare batteries n_h^s) and a flight schedule during day $d \in D$ at a hub $h \in H$, we aim to determine a charging schedule for batteries such that the charging schedule operating cost (electricity cost and flight delay cost) is minimized. For this, we need to determine which battery departs with which aircraft, and when to charge these batteries during the day. In the case that the infrastructure is not sufficiently large to ensure that flights depart on time, a penalty cost is incurred. This is a convex piecewise linear function of time, with breakpoints at T^{del} . Each time the flight delay is larger than some $\tau \in T^{del}$, a cost $c^{del}(\tau) \geq 0$ is incurred per unit of delay time. We assume that these delays are small and thus are assumed to be absorbed on route.

An overview of the model, with the interaction between the Battery charging station sizing problem and the Swapped aircraft batteries recharge scheduling problem, can be seen in Fig. 3. The latter is used as a subroutine in order to evaluate the charging schedule operation cost for a given infrastructure size on a single day.

4. A recourse model to optimize the charging infrastructure for swapped batteries

We propose a novel recourse model which manages the swapping and charging process for an airline operating a fleet of electric aircraft. This model is able to minimize the infrastructure and charging costs not just for a single day, but for an entire year of operations, consisting of the battery charging station sizing problem (long-term planning phase) and the swapped aircraft batteries recharge scheduling problem (medium-term planning phase). First, we propose a MILP which manages the charging schedule of the aircraft batteries, given a known flight schedule and charging infrastructure. This problem can be solved once a flight schedule

Table 1
Overview of used nomenclature.

| Sets | |
|---|--|
| D | Days |
| H | Hub airports |
| R | Regional airports |
| F_{arr}^{dh} | flights on day d arriving at hub h |
| F_{dep}^{dh} | flights on day d departing from hub h |
| B_{arr}^{dh} | batteries arriving with flights F_{arr}^{dh} |
| T_d | Time interval of day of operations d |
| T_d^* | Discretization of T_d |
| B_t^{dh} | batteries from B_{arr}^{dh} arrived by t |
| Input Parameters | |
| τ_a^{arr} | Arrival time of flight f |
| τ_a^{dep} | Departure time of flight f |
| τ^t | Transport time of batteries from aircraft to swapping stations |
| τ_b^s | Time battery $b \in B_{arr}^{dh}$ can start charging |
| τ_b^c | Recharge time of battery b |
| τ_f^c | Last time to charge a battery for departing flight f |
| P^c | Maximum battery charge rate |
| Charging capacity cost | |
| c^p | Charging capacity cost |
| Spare battery cost | |
| c^s | Spare battery cost |
| Electricity cost | |
| c^e | Electricity cost |
| Cost for flight delays greater than τ per unit of time | |
| $c^{del}(\tau)$ | Cost for flight delays greater than τ per unit of time |
| Discretization size of T_d^* | |
| Δt | Discretization size of T_d^* |
| Cumulative demand for charged batteries by $t \in T_d^*$ | |
| D_t^d | Cumulative demand for charged batteries by $t \in T_d^*$ |
| Number of overnight stay batteries | |
| n^o | Number of overnight stay batteries |
| Model variables | |
| $\tau_{bt}^c \in \mathbb{R}_+$ | Charging time of battery b during $[t, t + \Delta t]$ |
| $r_{bt} \in \{0, 1\}$ | Indicator: battery b fully charged by t |
| $S_t \in \mathbb{N}$ | Cumulative supply of charged batteries by t |
| $P_h \in \mathbb{R}_+$ | Charging capacity at hub h |
| $n_h^s \in \mathbb{N}$ | Number of spare batteries at hub h |
| $C_{dh} \in \mathbb{R}_+$ | Cost of charging operations for day d at hub h |
| $C_h \in \mathbb{R}_+$ | Charging infrastructure cost at hub h |

is made known, weeks before the day of operations. Second, we propose a master-problem to determine the most cost-effective charging infrastructure over an entire year of operations. This uses the swapped aircraft batteries recharge scheduling model as a subroutine. This problem is solved years in advance of the day of operations.

An overview of all used notation can be found in Table 1.

4.1. Tactical planning: Swapped aircraft batteries recharge scheduling problem

We first propose the swapped aircraft batteries recharging model, which considers a single day $d \in D$ and hub $h \in H$. The algorithm decides when each battery which arrives at the airport is charged, and to which outbound flight it is assigned. If, because of charging infrastructure limitations, batteries cannot be charged on time, outbound flights must wait until a fully charged battery is available. This formulation minimizes the sum of the cost for electricity used to charge the batteries and the cost of flight delays.

Let us first introduce the following notation for a hub $h \in H$. First, we discretize the day T_d in a set of intervals with length Δt . Let $T_d^{min} = \min(T_d)$ and $T_d^{max} = \max(T_d)$, the start and end of the day, respectively. As such we obtain $T_d^* = \{T_d^{min}, T_d^{min} + \Delta t, T_d^{min} + 2 \cdot \Delta t, \dots, T_d^{max}\}$. Second, we define the cumulative demand for charged batteries at time $t \in T_d^*$ as: $D_t^{dh} = |\{f \in F_{dep}^{dh} : \tau_f^c \leq t\}|$. This gives the total number of batteries which should have been charged by t in order to allow the flights to be performed on schedule. Third, a battery can only be charged once it has arrived at the charging station, and for each time $t \in T_d^*$, the set of these batteries is given by $B_t^{dh} = \{b \in B_{arr}^{dh} : t \leq \tau_b^s\}$.

At the start of T_d , a number of aircraft may already be present at the airport, which stayed there overnight. The batteries with which these arrived are assumed to have been fully recharged by the start of T_d . Let n^o denote the number of these batteries.

Decision variables

We consider the decision variable τ_{bt}^c , which gives the amount of time the battery b is charged during the interval $[t, t + \Delta t]$, with $t \in T_d^*$ and $b \in B_t^{dh}$. Additionally, we use the binary variables r_{bt} , which indicate if a battery has been fully charged by $t \in T_d^*$, with $b \in B_t^{dh}$. Finally, the integer variable S_t gives the cumulative amount of fully charged batteries by $t \in T_d^*$.

Mixed-integer linear problem formulation

We consider the following MILP to manage the recharging schedule at hub h , given a charging infrastructure (P_h, n_h^s) and a flight schedule on day d , which minimizes the operational costs $C_{dh}(P_h, n_h^s)$:

$$C_{dh}(P_h, n_h^s) = \min_{p,r,S} \sum_{t \in T_d} \left[\sum_{\tau \in T^{del}} (c^{del}(\tau) \cdot \max\{D_{t-\tau}^{fh} - S_t, 0\}) + c_t^e \sum_{b \in B_t^{dh}} \tau_{bt}^c P^c \right] \quad (1a)$$

$$\text{s.t.} \quad \sum_{t \in T_d^*} \tau_{bt}^c = \tau_b^c \quad \forall b \in B_{arr}^{dh} \quad (1b)$$

$$\tau_{bt}^c \leq \Delta t \quad \forall t \in T_d^*, b \in B_t^{dh} \quad (1c)$$

$$\sum_{b \in B_t^{dh}} \tau_{bt}^c \cdot P^c \leq \Delta t \cdot P_h \quad \forall t \in T_d^* \quad (1d)$$

$$1 - r_{bt} \geq |T_d|^{-1} \left[\tau_b^c - \sum_{t' \leq t} \tau_{bt'}^c \right] \quad \forall t \in T_d^*, b \in B_t^{dh} \quad (1e)$$

$$\sum_{b \in B_t^{dh}} r_{bt} + n_h^s + n^o = S_t \quad \forall t \in T_d^* \quad (1f)$$

$$\tau_{bt}^c \geq 0, r_{bt} \in \{0, 1\} \quad \forall t \in T_d^*, b \in B_t^{dh} \quad (1g)$$

The operational costs (Eq. (1a)) are given by the sum of the electricity costs, $c_t^e \sum_{b \in B_t^{dh}} \tau_{bt}^c P^c$, and the aircraft delays incurred, $\sum_{\tau \in T^{del}} (c^{del}(\tau) \max\{D_{t-\tau}^{fh} - S_t, 0\})$, for each interval $[t, t + \Delta t]$ with $t \in T_d^*$. Constraints (1b) ensure that all batteries which arrive at the airport are charged by the end of the day, ensuring a supply of spare batteries on the next day. Constraints (1c) ensure that during each interval, batteries are not charged longer than the length of the interval, whereas Constraints (1d) ensure that the total charging capacity is not exceeded. Whether or not a battery is ready to be used on an outbound flight by t is determined in Constraints (1e), which force r_{bt} to be 0 as long as battery b is not fully charged. Finally, Constraints (1f) determine the cumulative supply of spare batteries.

4.2. Strategic planning: battery charging station sizing problem

Second, we propose a recourse model which optimizes the charging infrastructure size, given the flight schedules which reflect the traffic demand variation during an entire year of operations D . This functions as the master problem of the recourse model, and is solved only once for the entire year. It determines the expected operational cost of a charging infrastructure by using the optimization model from Section 4.1 as a subroutine. These operational costs are added to the capital expenditures, i.e., the cost of acquiring and maintaining chargers and spare batteries to obtain the total costs, which we aim to minimize.

Decision variables

We consider the decision variables $P_h \in \mathbb{R}^+$ and $n_h^s \in \mathbb{N}$, the charging capacity and the number of spare batteries at hub airport h , respectively.

Recourse model formulation

We consider the following MILP to determine the suitable charging infrastructure size at a hub, given the distribution of flight schedules D , which minimizes the total cost C_h :

$$C_h = \min_{P_h, n_h^s} c^p P_h + c^s n_h^s + \sum_{d \in D} C_{dh}(P_h, n_h^s) / |D| \quad (2a)$$

$$P_h \geq 0 \quad (2b)$$

$$n_h^s \in \mathbb{N} \quad (2c)$$

In this formulation, C_h is the sum of the daily cost of the charging capacity, $c^p P_h$, the spare batteries $c^s n_h^s$, and the average operational costs $\sum_{d \in D} C_{dh}(P_h, n_h^s) / |D|$, which is obtained from the tactical planning problem of Section 4.1 for each day $d \in D$.

Simulated annealing algorithm

The value of $\sum_{d \in D} C_{dh}(P_h, n_h^s)$ cannot be evaluated trivially, hence regular MILP solution algorithms are unsuitable to solve this problem. As $\sum_{d \in D} C_{dh}(P_h, n_h^s)$ is also non-convex in P_h and n_h^s , we use Simulated Annealing to find an approximate solution. The approach we use to optimize the airport charging infrastructure is given in Algorithm 1.

The algorithm first obtains an initial solution (lines 2–9). The expected operating costs for each solution are determined. After the initial solution is found, the algorithm iterates towards better solutions by selecting a solution in the neighborhood of the current solution (line 11), evaluating the expected operating costs only for the current solution (line 12). The new solution is accepted if it is an improvement over the current one (line 14), or with a probability less than one if it is not (line 16, to avoid being stuck in local optima). This process continues until a stopping criterion is met.

Algorithm 1: Simulated Annealing algorithm to optimize airport battery charging infrastructure

Data: Hub h , Days with flights D , c^p , c^s , c^e , c^{del} , $(n_{min}^s, \Delta n^s, n_{max}^s)$, $(P_{min}, \Delta P, P_{max})$, $\Lambda_s, \Lambda_e, \alpha$

Result: Minimum cost charging capacity \hat{P} and number of spare batteries \hat{n}^s

- 1 Initialize $\hat{P} = 0$, $\hat{n}^s = 0$, $\hat{C} = \infty$ and $\Lambda = \Lambda_s$;
- 2 Let $n^{s*} = \{n_{min}^s, n_{min}^s + \Delta n^s, \dots, n_{max}^s\}$;
- 3 Let $P^* = \{P_{min}, P_{min} + \Delta P, \dots, P_{max}\}$;
- 4 **for** $(n^s, P) \in n^{s*} \times P^*$ **do**
- 5 Determine $C_h(P, n^s) = c^p P + c^s n^s + \sum_{d \in D} C_{dh}(P, n^s)/|D|$;
- 6 **if** $C_h(P, n^s) \leq \hat{C}_h$ **then**
- 7 | Set $\hat{P} \leftarrow P$, $\hat{n}^s \leftarrow n^s$ and $\hat{C}_h \leftarrow C_h(P, n^s)$;
- 8 **end**
- 9 **end**
- 10 **while** $\Lambda \geq \Lambda_e$ **do**
- 11 Select $\tilde{P} \in \hat{P} + [-\Delta P, \Delta P]$ and $\tilde{n}^s \in \hat{n}^s + [-\Delta n^s, \Delta n^s]$ randomly;
- 12 Determine $C_h(\tilde{P}, \tilde{n}^s) = c^p \tilde{P} + c^s \tilde{n}^s + \sum_{d \in D} C_{dh}(\tilde{P}, \tilde{n}^s)/|D|$;
- 13 **if** $\tilde{C}_h(\tilde{P}, \tilde{n}^s) < \hat{C}_h$ **then**
- 14 | Accept the new solution (\tilde{P}, \tilde{n}^s) ;
- 15 **else**
- 16 | Accept the new solution (\tilde{P}, \tilde{n}^s) with probability $p = e^{-(\tilde{C}_h(\tilde{P}, \tilde{n}^s) - \hat{C}_h)/\Lambda}$;
- 17 **end**
- 18 **if** We accept the new solution **then**
- 19 | Set $\hat{P} \leftarrow \tilde{P}$, $\hat{n}^s \leftarrow \tilde{n}^s$, and $\hat{C}_h \leftarrow \tilde{C}_h(\tilde{P}, \tilde{n}^s)$;
- 20 **end**
- 21 Set $\Lambda \leftarrow \alpha \Lambda$;
- 22 **end**

5. Case study: optimizing the charging infrastructure for Widerøe Airlines (Norway)

In this section, we apply the model presented in Section 4 to the short-haul flight network of Norwegian Widerøe Airlines, using flight schedule based on the performed flights during October 2021–October 2022.

We use the case of Widerøe Airlines because Norway has a strong position for early implementations of electric aircraft on commercial flights. Due to the challenging terrain, air transport is often the only viable means of travel. This results in a market with a lot of low-passenger short-haul flights: around 77% of all domestic flights in the country are under 400 km (Bærheim et al., 2022). In addition, Norway's electricity is for 98% produced with renewable resources (Olje- og energidepartementet, 2016) such that the electric aircraft can be operated sustainably.

The experiment was performed by implementing the algorithm with Gurobi Optimizer 9.1, on an Intel Core i7-10610U with 8 GB of RAM.

Short-haul network of Widerøe Airlines

Widerøe Airlines is the largest commuter operator in Scandinavia (Bærheim et al., 2022). It operates a fleet of 23 De Havilland Canada Dash 8–100 aircraft (hereafter: Dash 8) for short-haul flights within and to Norway. These have a capacity of 40 passengers or a payload of 4500 kg. These aircraft account for the majority of Widerøe's fleet. We propose a scenario in which this fleet is replaced with electric aircraft, while keeping to the existing flight schedule as much as possible. We have imported the flight data for the Dash 8 between 28 October 2021 and 27 October 2022, using data from Flightradar24 (2022) for each aircraft of the Dash 8 fleet. We have used the actual time of departure, actual landing time, origin and departure of each flight. As such, cancelled flights have not been included in the data. The network spanned by these aircraft consists of 43 airports and 56,000 flights; it is shown in Fig. 4.

The used flight schedules in this case study are based on the analyzed historical flight data. We assume that all itineraries between hubs (possibly via regional airports) which were previously performed by the Dash 8 and are within range of the electric aircraft, are performed by the e-AC. The e-AC start each journey from a hub airport with a fully charged battery. If there are any stopovers at non-hub airports, it will recharge its battery during turnaround. This is done using the existing ground power infrastructure. Last, if there are two subsequent flights for an aircraft, from A to B and from B to C, and the first flight cannot be performed on time (due to battery/charging limitations), then the aircraft directly flies from A to C. Flights A to B and B to C are not included in the schedule. We use these as our (365) flight schedules.

Assuming a range of 610 km (see the next subsection on the e-AC model) approximately 52,000 of the 56,000 flights which we have analyzed can be performed by the electric aircraft. A comparison of the number of flights visiting the 20 busiest airports can be seen in Fig. 5. We propose to use the seven most visited airports in the network as hubs for the electric aircraft fleet, where batteries can be swapped. These airports are in the towns of Bodø (BOO, 15,000 flights annually), Tromsø (TOS, 10,000 flights), Trondheim

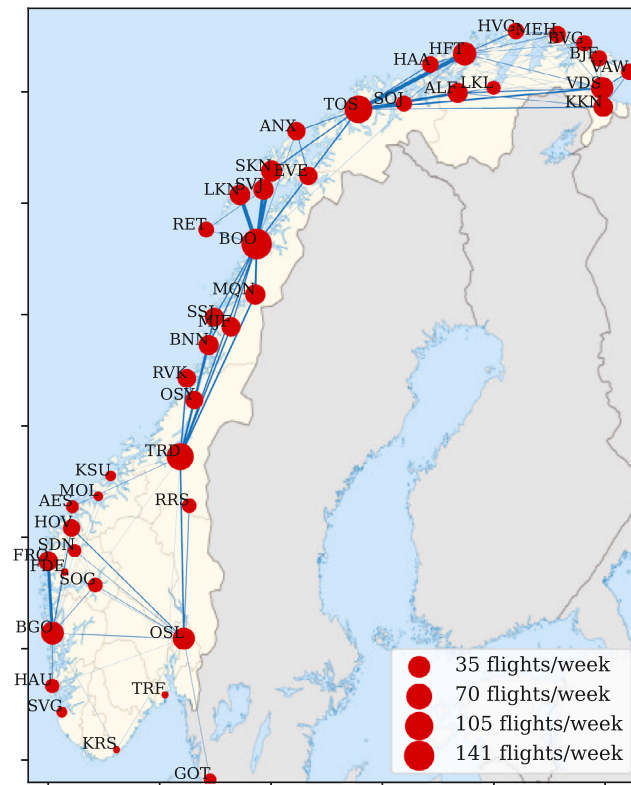


Fig. 4. Network of the Dash 8–100 of Widerøe airlines, flown between the 28th of October 2021 and the 27 of October 2022.

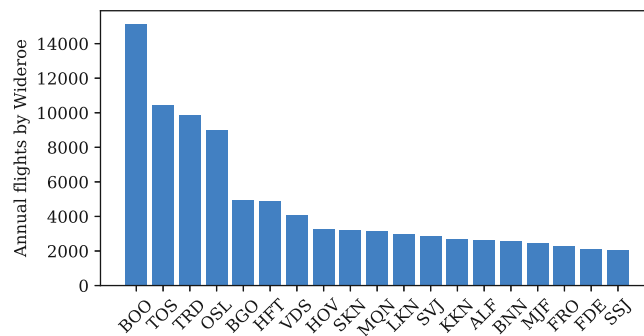


Fig. 5. Histogram of number of annual flights at the twenty most visited hubs of Widerøe. Flight data between October 28, 2021 and October 27, 2022 is used.

(TRD, 10,000 flights), Oslo (OSL, 9000 flights), Bergen (BGO, 5000 flights), Hammerfest (HFT, 5000 flights) and Vadsø(VDS, 4000 flights). Table 2 shows the distribution of the number of daily flights on each of the selected hubs. Even though there is a significant variance in the number of daily flights, there is no seasonal difference for this fleet. This is because the Dash-8 100 aircraft are mainly used for commuting and to deliver cargo, and only to a lesser degree for tourism.

Specifications of the electric aircraft

We propose a scenario where the Dash-8 aircraft are replaced by an e-AC with the specifications of the Eviation Alice (Eviation, 2022). Currently in the certifying phase, the Alice is able to transport ten passengers or a payload of 1150 kg.

The Alice is currently able to fly a distance of 250 nm (approximately 480 km). Assuming a continuation of current battery development (Ziegler and Trancik, 2021), this will increase to 610 km by 2025. It is equipped with a 820 kWh battery which requires slightly over 4 h for a full recharge. We assume that the charging power available at hubs and regional airports is the same. The cruising speed of 260 kts is comparable to the 280 kts of the Dash 8–100, and as such we assume the flight duration is unchanged. We assume that 7% of the battery capacity is required for take-off (Hepperle, 2012). All used characteristics of the

Table 2

Daily flight statistics at the considered hubs of Widerøe. The average, median, standard deviation and maximum of the number of daily flights is given. Flight data between October 28, 2021 and October 27, 2022 is used.

| Hub airport | | Daily flights | | | |
|---------------|------------|---------------|--------|------|------|
| IATA | City | average | median | std | peak |
| BGO | Bergen | 9.4 | 10 | 4.2 | 22 |
| BOO | Bodø | 29.7 | 32 | 11.5 | 55 |
| HFT | Hammerfest | 12.8 | 13 | 6.7 | 27 |
| OSL | Oslo | 14.6 | 9 | 3.5 | 19 |
| TOS | Tromsø | 24.7 | 26 | 10.6 | 49 |
| TRD | Trondheim | 21.8 | 21 | 8.5 | 40 |
| VDS | Vadsø | 9.9 | 10 | 4.7 | 22 |
| Network total | | 122.9 | 125 | 43.9 | 184 |

Table 3

Eviation Alice performance and economic parameters.

| Aircraft specifications | | Economic assumptions | |
|------------------------------|------------------------------------|---------------------------|---|
| Battery capacity | 820 kWh (Eviation, 2022) | Spare battery cost | 80 €/day (Justin et al., 2020) |
| Range | 610 km (Adu-Gyamfi and Good, 2022) | Charging capacity cost | 0.4 €/kW/day (Justin et al., 2020) |
| Maximum power | 2×700 kW (Eviation, 2022) | Delay cost | 9.05–29.90 €/min Cook and Graham (2015) |
| Maximum charging power | 200 kW (Hepperle, 2012) | Peak electricity price | 0.134 €/kWh (sentralbyrå, 2022) |
| Take-off and climbing energy | 60 kWh (Hepperle, 2012) | Peak-hours | 7 AM–8 PM (Nordpool Group, 2022) |
| Battery transport time | 30 min | off-peak electricity cost | 0.067 €/kWh (Nordpool Group, 2022) |
| Final reserve | 120 kWh (Eviation, 2022) | | |

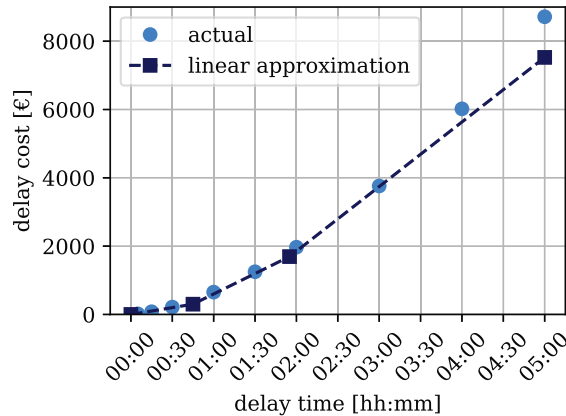


Fig. 6. Actual and piece-wise linear approximation of the flight delay costs. The actual costs are based on European reference values for the ATR-43 (Cook and Graham, 2015).

aircraft can be found in Table 3. The electricity cost is derived from historical data (Nordpool Group, 2022), and a resolution of $\Delta t = 15$ min has been used.

Flight delay costs are derived from European industry data (Cook and Graham, 2015), which takes flight personnel, maintenance, fuel and passenger costs into account. We use the tactical costs of the ATR-43 as reference and scale them to account for the difference in size (10 passengers instead of 42) and inflation (20%). Using $\tau^{del} = \{00:00, 00:45, 01:15\}$, we have found $c^{del}(0:00) = \text{€}9.05$, $c^{del}(0:45) = \text{€}10.90$, and $c^{del}(1:15) = \text{€}10.95$. The original data and this approximation are shown in Fig. 6.

Because of this, the payload is about a quarter of the size of the payload of Dash 8. In this paper we aim to maintain the original flight schedule without optimizing for the difference in the payload. This would required adding more flights to the schedule, and is addressed in Section 5.2.

5.1. Results—optimizing the charging infrastructure for widerøe airlines

We apply the optimization framework from Section 4 to the flight network of Widerøe Airlines and the e-AC model to obtain the most cost-effective charging infrastructure at the 7 hub airports. We first discuss the results for the largest hub, Bodø, in detail. After this, we shall present the results for all hubs.

Table 4

Infrastructure (charging capacity [P_h] and spare batteries [n_h^s]), average operational characteristics and costs (electricity and caused hours of delay) at Bodø Lufthavn.

| | | | Size | Costs [€] |
|----------------|-------------------------|---------|-------|-----------|
| Infrastructure | Charging capacity P_h | [kW] | 900 | 360 |
| | Spare batteries n_h^s | [-] | 6 | 1500 |
| Operations | Energy consumption | [kWh] | 8950 | 890 |
| | Delays | [hh:mm] | 00:12 | 140 |
| Total | | | - | 2943 |

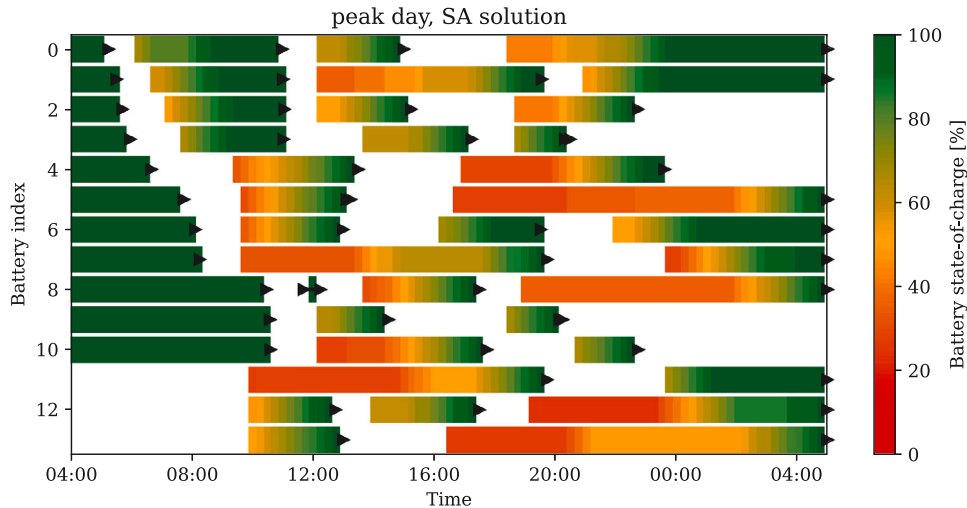


Fig. 7. Optimal recharging schedule of the swapped batteries at Bodø Lufthavn on the peak traffic day (August 25, 2022), using $P_h = 900$ kW and $n_h^s = 6$. Each bar represents a battery, which starts and ends when it arrives at and departs from the charging station, respectively. The color of the bar indicates the current battery state-of-charge. Each arrow shows the scheduled and actual departure time of the flights to which the batteries are assigned.

5.1.1. Bodø Lufthavn

Bodø Lufthavn is the most frequently visited airport in the network of Widerøe Airlines, and serves as a hub to connect the north of Norway with the south. The daily amount of traffic ranges up to 55 flights (on August 25, 2022) with a median of 32 (on a.o. July 13, 2022) and an average of 29.7.

We have determined the most cost-effective charging infrastructure at Bodø Airport: $(P_h, n_h^s) = (900 \text{ kW}, 6)$. This requires an investment of $c^p P_h + c^s n_h^s = \text{€}1840$ per day. Table 4 shows the optimal infrastructure size, operational characteristics, and costs on average over all days. In addition to the €1840 daily infrastructure investment, there are €1030 daily operational costs. These are mainly due to the electricity costs (8950 kWh consumption for €890) with average delays fairly minimal. On average over all days, the aircraft at Bodø are delayed for a total of 12 minutes, showing how much the optimal solution prefers to avoid disrupting the flight schedule.

Fig. 7 shows the most efficient battery recharge schedule on the peak day (August 25, 2022), using the optimized infrastructure. Each bar in the figure represents a battery. The bar starts and ends when the battery arrives and departs from the charging station. The row in which a battery is placed is irrelevant: different batteries are placed on the same row in order to limit the number of rows in the figure. The color of the bar indicates the current state-of-charge. Additionally, the black arrows show the scheduled and actual departure times of the flights to which the batteries are assigned. At the start of the day, 11 batteries are available at the airport (six spare batteries and five batteries from flights which arrived on the previous day). As can be seen, batteries which are fuller when they arrive tend to be charged first, whereas the batteries which take longer to charge tend to spend more idle time at the airport. Also, three flight experience a delay, two of which are limited (15 min delay) and one is more severe (45 min). At the end of the day, 9 batteries (of which 6 are spares) remain at the airport. Given that these delays are in the order of a couple of minutes on the peak traffic day, we assume that these are absorbed en-route in the next leg.

The charging schedules on the peak traffic day (August 25, 2022) and a median traffic day (July 13, 2022) are further detailed in Fig. 8. The spare battery stock (or backlog) is shown in the top row, and the electricity consumption and price are shown in the bottom row. On the median traffic day, there is almost always a fully charged spare battery in stock. Additionally, a large portion of the charging is done during the off-peak electricity pricing hours: only the bare minimum of charging is performed between 3 PM and 8 PM, after which it uses the full charging capacity. Contrasting this, the full charging capacity is almost constantly used on the peak day. As a result, battery backlog remains limited even though there is almost never a charged battery available during 10 AM and midnight. The longer delay from Fig. 7 can be seen as battery backlog just before 12 PM. The fact that delays remain minimal even on the peak day shows the robustness of this infrastructure size.

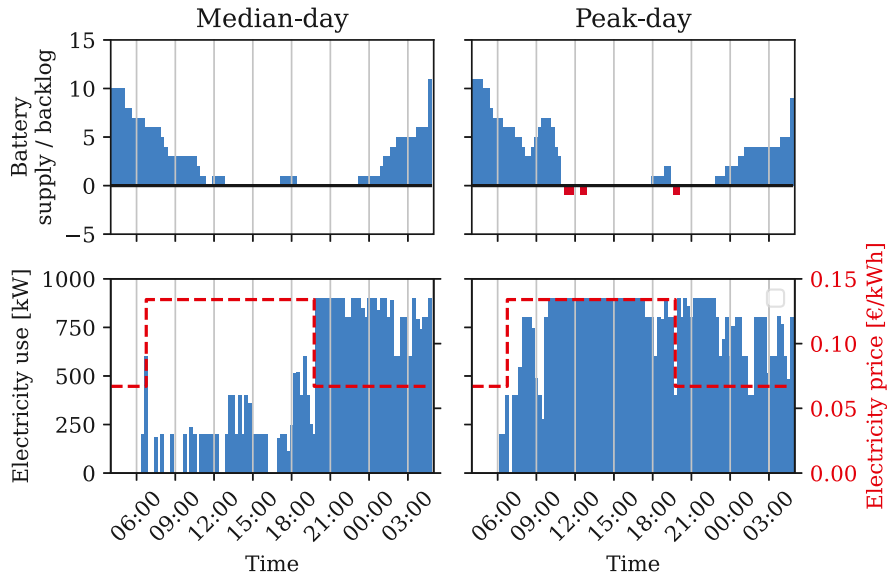


Fig. 8. Battery supply and backlog and electricity use and price throughout the median (July 13th, 2022) and peak (August 25th, 2022) days of operations at Bodø Lufthavn, using $P_h = 900$ kW and $n_h^s = 6$.

Table 5

Infrastructure and expected operational cost for the considered hubs in the network. The first column lists the airport codes and average daily number of flights. Here, C_h^e and C_h^{del} give the average daily electricity and delay cost.

| Hub airport Airport h | Flights | Infrastructure | | Operations | | Average cost | | | | |
|----------------------------|---------|----------------|---------|------------|---------|--------------|-------------|---------|-------------|-------|
| | | P_h | n_h^s | Energy | Delays | $c^p P_h$ | $c^s n_h^s$ | C_h^e | C_h^{del} | C_h |
| [–] | [–] | [kW] | [–] | [kWh] | [hh:mm] | [€] | [€] | [€] | [€] | [€] |
| BGO Bergen | 9.4 | 425 | 2 | 3553 | 00:13 | 170 | 500 | 300 | 123 | 1093 |
| BOO Bodø | 29.7 | 900 | 6 | 8950 | 00:12 | 360 | 1500 | 890 | 140 | 2890 |
| HFT Hammerfest | 12.8 | 413 | 2 | 2430 | 00:06 | 160 | 500 | 240 | 70 | 970 |
| OSL Oslo | 14.6 | 612 | 3 | 4410 | 00:09 | 245 | 750 | 460 | 95 | 1550 |
| TOS Tromsø | 24.7 | 812 | 4 | 6303 | 00:11 | 325 | 1000 | 642 | 120 | 2087 |
| TRD Trondheim | 21.8 | 850 | 5 | 7330 | 00:09 | 340 | 1250 | 744 | 101 | 2478 |
| VDS Vadsø | 9.9 | 400 | 2 | 255 | 00:14 | 160 | 500 | 260 | 142 | 1062 |
| Network total | 122.9 | 4412 | 25 | 33231 | 01:14 | 1600 | 6000 | 3392 | 801 | 11793 |

5.1.2. Charging infrastructure at Bergen, Bodø, Hammerfest, Oslo, Tromsø, Trondheim and Vadsø

Table 5 shows the optimized infrastructure, together with the average operations energy consumption, delays and costs for all seven hubs. The daily costs range from €970 at Hammerfest Lufthavn (HFT) up to €2890 at Bodø Lufthavn, accumulating to a network total of €11,793 per day. It should be kept in mind that this does not account for the decrease in payload caused by using 10-seater aircraft instead of the 37-seater Dash-8. The table shows an approximate marginal cost of €100 per flight, which is independent of the difference in payload, of which the spare battery supply forms the biggest share. Furthermore, the delay costs are not proportional to the number of daily flights. For example, the average delay costs at Vadsø of €142 are larger than the costs at Bodø, of €140, which accommodates three times the number of flights.

5.2. Sensitivity analysis: battery capacity and daily number of flights

We perform a sensitivity analysis to assess the impact of the technological and economical assumptions we have made on the results. This is done for the development of battery energy density and the daily number of flights. We evaluate the impact of these on the optimal infrastructure, as well as the computational requirements to solve the problems. We show the results for Bodø Airport.

Table 6 shows the impact of the aircraft battery performance. We assume that the energy density of the batteries increases by an annual rate of 8% (Ziegler and Trancik, 2021), resulting in a 610 km flight range. We compare this rate with a pessimistic scenario of 0% (range of 480 km) annual increase of the energy density, 4% (range of 540 km), 12% (range of 685 km) and 16% annual increase (range of 775 km). Table 6 shows the required infrastructure, investment, as well as the total optimization time and average optimization time per day subroutine.

Table 6

Optimal charging infrastructure at Bodø Airport given various battery energy densities. Both the computational time of the infrastructure optimization and the average per daily recharge scheduling optimization are given. The green case represents the nominal case considered in Section 5.1.1.

| Battery development | | Infrastructure | | Operations | | Cost | Computational time | |
|---------------------|---------------------------|----------------|---------|------------|--------|-------|--------------------|----------|
| Range | Average # Flights per Day | P_h | n_h^s | Energy | Delays | C_h | total | instance |
| km | – | kW | – | kWh | hh:mm | € | mm:ss | s |
| 480 | 22.3 | 755 | 5 | 6010 | 00:03 | 1862 | 21:05 | 0.403 |
| 540 | 29.6 | 865 | 7 | 8680 | 00:09 | 2796 | 24:24 | 0.451 |
| 610 | 29.7 | 900 | 6 | 8950 | 00:12 | 2890 | 26:00 | 0.459 |
| 685 | 29.8 | 1145 | 5 | 9270 | 00:10 | 3036 | 26:12 | 0.472 |
| 775 | 29.9 | 1345 | 5 | 9624 | 00:10 | 3566 | 26:29 | 0.480 |

Table 7

Optimal charging infrastructure at Bodø Airport given various average number of flights per day. Both the computational time of the infrastructure optimization and the average per daily recharge scheduling optimization are given. The green case represents the nominal case considered in Section 5.1.1.

| Schedule | | Infrastructure | | Operations | | Cost | Optimization time | |
|---------------------------|---|----------------|---------|------------|--------|-------|-------------------|--------------|
| Average # Flights per Day | – | P_h | n_h^s | Energy | Delays | C_h | total | per instance |
| – | – | kW | – | kWh | hh:mm | € | min | s |
| 30 | – | 900 | 6 | 8950 | 00:12 | 2890 | 26 | 0.459 |
| 60 | – | 1740 | 12 | 17900 | 00:15 | 5651 | 51 | 0.911 |
| 89 | – | 2410 | 17 | 26850 | 00:21 | 8075 | 108 | 1.90 |
| 119 | – | 3190 | 23 | 35800 | 00:27 | 10837 | 201 | 3.49 |

The results show that above 540 km, range no longer is a limiting factor on the number of flights, stabilizing at around 29.6–29.8. Above this number, the energy requirements increase linearly, affecting the total costs. Only in the most pessimistic scenario (range of 480 km), the range does impede the flight schedule, reducing the number of daily flights by a quarter. In this case, the entire infrastructure is reduced in size and the costs decrease by a third. Finally, in all cases, the computational time is limited to under 30 min for the entire algorithm, and under half a second for each day of operations.

Table 7 shows the impact of the number of electric flights performed on the infrastructure and costs. We assumed that the original schedule is adhered as much as possible, but this does decrease the total payload which can be carried to about 25% of the original schedule. We compare this with 50%, 75% and 100% by doubling, tripling, and quadrupling the number of times each flight is performed. Table 7 shows the average number of flights at Bodø, the infrastructure requirements and costs, and the optimization time.

The results show a sub-linear increase of the costs as a function of number of flights. The infrastructure does grow approximately linear with the number of flights, but the delays remain fairly limited. The computational time increased from 26 to 201 min for the infrastructure optimization and from 0.46 to 3.5 s for each recharge scheduling optimization.

6. Quantifying the benefit of recourse optimization considering air traffic for an entire year vs. infrastructure optimization considering only one day of traffic

6.1. Infrastructure optimization considering only a peak-day or a median-day of air traffic

In order to assess the performance of the recourse model proposed in Section 4.2, we consider two alternative battery charging infrastructure optimization approaches. These approaches optimize the infrastructure using only the flight schedule from a single day of operations. For this, we use either the peak traffic day (PD) or a median traffic day (MD), according to the total number of flights. Using a peak-day flight schedule corresponds to the desire to obtain an infrastructure which is able to cope with the most congested days, although this expensive infrastructure may be overly large during less busy days. Using a median day as reference leads to obtaining an infrastructure which performs well on most days of operations but may be insufficient during congested days.

The two alternative infrastructure optimization approaches use a version of the MILP from Section 4.1 modified in two respects. First, the charging capacity P_h and the number of spare batteries n_h^s are model variables instead of input parameters. Second, their associated costs (c^p and c^s) are included in the objective function. As such, the following model is considered:

$$C_{dh}^{SD} = \min_{P_h, n_h^s, \tau, r, S} c^p P_h + c^s n_h^s + \sum_{t \in T_d}^* \left[\sum_{\tau \in \tau^{del}} \left(c^{del}(\tau) \cdot \max\{D_{t-\tau}^{fh} - S_t, 0\} \right) + c_t^e \sum_{b \in B_t^{dh}} \tau_{bt}^c P^c \right] \quad (3a)$$

$$(1b) - (1g) \quad \vdots$$

$$P_h \geq 0, n_h^s \in \mathbb{N} \quad (3b)$$

Table 8

Infrastructure and average electricity consumption and flight delays at Bodø Lufthavn, with their associated daily costs ($c^P P_h^x$, $c^S n_h^{s,x}$, $C^{e,x}$, and $C^{del,x}$, respectively) for three infrastructures x . We consider the recourse optimization model (YR) vs. the optimization model for only one peak-traffic day SD(PD) and only one median-traffic day SD(MD). The PD is August 25th, 2022. The MD is July 13th, 2022. For (*) there are on average 29.7 flights/day considering the entire year of operations.

| Solution x | Flights | Infrastructure | | Operations | | Average Cost | | | | |
|--------------|---------|-----------------|--------------------|-----------------|-------------------|--------------------|------------------------|------------------|--------------------|--------------|
| | | P_h^x [kW] | $n_h^{s,x}$ [-] | Energy [kWh] | Delays [hh:mm] | $c^P P_h^x$ [€] | $c^S n_h^{s,x}$ [€] | $C^{e,x}$ [€] | $C^{del,x}$ [€] | C^x [€] |
| $S(YR)$ | 29.5* | 900 | 6 | 8950 | 0:12 | 360 | 1500 | 890 | 140 | 2890 |
| $S(PD)$ | 55 | 1130 | 7 | 8950 | 00:05 | 430 | 1750 | 870 | 80 | 3140 |
| $S(MD)$ | 32 | 800 | 4 | 8950 | 02:36 | 320 | 1000 | 950 | 1925 | 4195 |

The objective function, Eq. (1a), has been replaced by Eq. (3a), and now computes the most cost-effective infrastructure for a single day d at hub h . The corresponding cost is denoted as $C_{dh}^{S,D}$. Constraints (1b)–(1g) are unaltered, and Constraint (3b) has been added to the model.

6.2. Results: quantifying the advantage of recourse infrastructure optimization for Widerøe Airlines at Bodø

We quantify the cost reduction gained by using the infrastructure optimized by the recourse MILP for Widerøe Airlines at Bodø Lufthavn. This original solution (see Section 5.1.1) takes the year-round flight schedule into account and is referred to as the $S(YR)$ solution hereafter. We compare it with optimized infrastructure for the peak- and median levels of traffic days of operations, using the algorithm from Section 6.1. For the peak- and median traffic days, we have used PD = August 25, 2022, with 55 flights, and MD = June 13, 2022, with 32 flights. The infrastructure solutions obtained with only these single days are referred to as the $S(PD)$ and $S(MD)$ solutions, respectively.

The three charging infrastructure solutions can be found in Table 8. For each solution $x \in \{S(YR), S(MD), S(PD)\}$ the size of the different components is shown, together with the expected costs, similar to Table 5. The peak-traffic day optimized infrastructure consists of $(P_c^{S(PD)}, n_h^{s,S(PD)}) = (1130 \text{ kW}, 7)$, resulting in a daily infrastructure cost of €2180. It was computed in 12.7 s. The median-traffic day optimized infrastructure consists of $(P_c^{S(MD)}, n_h^{s,S(MD)}) = (800 \text{ kW}, 4)$ resulting in a daily infrastructure cost of €1320. This was computed in 5.7 s.

The total average daily costs of each solution x is given as:

$$C^x = c^P P_h^x + c^S n_h^{s,x} + \sum_{d \in D} C_{dh}(P_h^x, n_h^{s,x})/|D| \quad (4)$$

For our analysis, $C^{S(YR)} = \text{€}2890$, compared to $C^S = \text{€}4730$ (+58%) for the $S(MD)$ solution and $C^{S(PD)} = \text{€}3140$ (+6%) for the $S(PD)$ solution. Table 8 shows a breakdown of the costs, split up into charging capacity, spare battery, electricity and delay costs. Compared with the $S(YR)$ solution, the $S(PD)$ solution trades charging capacity for an extra battery and a significantly larger infrastructure investment, but reduces the expected delays and is able to profit from slightly lower electricity costs. On the other hand, the $S(MD)$ solution consists of a relatively small charging capacity, but causes significant flight delays (on average a total of 2:36 h daily).

Last, Fig. 9 shows the cost of the three infrastructure solutions depending on the number of flights on the days of operation. Each point represents one of the 356 days of operations, which are sorted by number of flights. Generally speaking, the daily costs increase with the number of flights. Additionally, the $S(MD)$ and $S(YR)$ infrastructures are stressed more for a large number of flights than the $S(PD)$ infrastructure.

Note that for a small number of flights, not the $S(MD)$ but the $S(YR)$ solution has the lowest total costs, aided by the flexibility of a larger charging capacity. For busier days, the $S(PD)$ solution starts to outperform the other two, with the costs of the $S(YR)$ and $S(MD)$ solutions increasing to €5000 and €24,000 (not on chart), respectively.

7. Conclusions

This paper proposes a two-phase recourse model optimization framework for battery swap and recharge operations for an airline operating a fleet of short-haul electric aircraft. This framework integrates the scheduling of swapped battery recharges with the sizing of the recharge infrastructure, without merging them completely to account for the fact that the infrastructure size cannot be altered daily. The objective for the former is to minimize the charging station operational costs, comprised of the electricity and the caused delay cost. For the latter, the objective is to minimize the sum of the infrastructure acquisition cost and the average operational cost throughout the year. The scheduling problem, posed as a mixed-integer linear program, is used as a subroutine for the infrastructure sizing problem, which is solved using a simulated annealing algorithm.

Our optimization framework is applied in a case study for Norway's Widerøe Airlines, where the airline's fleet of DHC Dash 8–100 aircraft is replaced with a fleet of electric aircraft based on Eviation Alice's specifications. We use flight data from 28 October 2021 and 27 October 2022 and keep to the original schedule as much as possible. It is assumed that the aircraft will be able to swap their batteries at the seven most visited airports in the network, such that approximately 52,000 out of the 56,000 analyzed flights can be performed. The results show that a combined power supply consists of 4412 kW and that 25 spare batteries are required, such

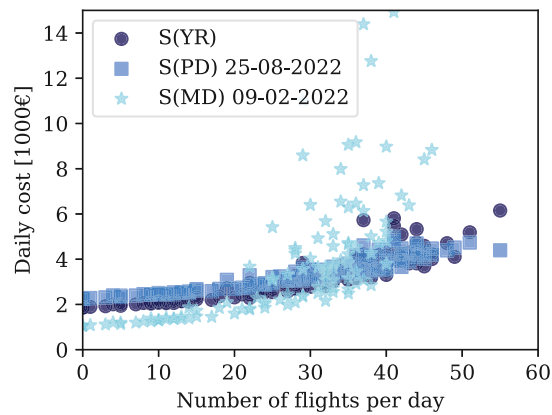


Fig. 9. Daily infrastructure costs $C_{dh}(P_h^x, n_h^{s,x})$ when considering $(P_h^{S(YR)}, n_h^{s,S(YR)}) = (900 \text{ kW}, 6)$, $(P_h^{S(PD)}, n_h^{s,S(PD)}) = (1130 \text{ kW}, 7)$, and $(P_h^{S(MD)}, n_h^{s,S(MD)}) = (800 \text{ kW}, 4)$, during the period 28th October 2021–27th October 2022. Each point represents a single day of operations.

that the daily cost of this charging infrastructure is €11,793. However, this analysis does not account for the decrease in payload which results from replacing the 40-seats Dash-8 with the 10-seats Alice. The actual infrastructure cost are bounded from above by multiplying the found values by a factor of 4.

We also propose two baseline infrastructure sizing solutions, which minimize the charging infrastructure size given only one day of operations: the peak- or median-traffic day. Overall, these approaches achieve an optimality gap of 8% and 45%, respectively. Infrastructure optimized for the peak day tends to be oversized on average, resulting in high capital expenditures but relatively low operational costs. Infrastructure optimized for the median day, on the other hand, is used well on average days but results in major flight delay on peak load days.

As future work, we plan to extend the model for an airline operating different e-AC models with different specifications and charging needs. Second, when applied to an airline with seasonality in the flight schedule, the option of a seasonally varying spare battery stock can be studied. It will also introduce the arrival and departure time of flights not as fixed but as stochastic variables. Using this information can help to create a more realistic assessment of the performance of the charging infrastructure. Finally, we plan to improve our model to identify the most suitable airports to place the battery swapping stations, rather than all hub airports.

CRediT authorship contribution statement

Simon van Oosterom: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Mihaela Mitici:** Conceptualization, Methodology, Validation, Investigation, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- Adu-Gyamfi, B.A., Good, C., 2022. Electric aviation: A review of concepts and enabling technologies. *Transp. Eng.* 9, 100134. <http://dx.doi.org/10.1016/j.treng.2022.100134>.
- Asadi, A., Nurre Pinkley, S., 2021. A stochastic scheduling, allocation, and inventory replenishment problem for battery swap stations. *Transp. Res. E* 146, 102212. <http://dx.doi.org/10.1016/j.tre.2020.102212>.
- Ayad, A., El-Taweel, N.A., Farag, H.E.Z., 2021. Optimal design of battery swapping -based electrified public bus transit systems. *IEEE Trans. Transp. Electr.* 7 (4), 2390–2401. <http://dx.doi.org/10.1109/TTE.2021.3083106>, Conference Name: IEEE Transactions on Transportation Electrification.
- Bærheim, T., Lamb, J.J., Nøland, J.K., Børheim, O.S., 2022. Potential and limitations of battery -powered all -electric regional flights –A Norwegian case study. *IEEE Trans. Transp. Electr.* 1. <http://dx.doi.org/10.1109/TTE.2022.3200089>, Conference Name: IEEE Transactions on Transportation Electrification.
- Balogun, M.-S., Yang, H., Luo, Y., Qiu, W., Huang, Y., Liu, Z.-Q., Tong, Y., 2018. Achieving high gravimetric energy density for flexible lithium-ion batteries facilitated by core–double-shell electrodes. *Energy Environ. Sci.* 11 (7), 1859–1869. <http://dx.doi.org/10.1039/C8EE00522B>, Publisher: The Royal Society of Chemistry.
- Brdnik, A.P., Kamnik, R., Bozicnik, S., Marksel, M., 2022. Ground infrastructure investments for operation of hybrid-electric aircraft. In: *IOP Conference Series: Materials Science and Engineering*, Vol. 1226, No. 1. 012073. <http://dx.doi.org/10.1088/1757-899X/1226/1/012073>, Publisher: IOP Publishing.
- Cook, A., Graham, T., 2015. European airline delay cost reference values. Tech. Rep., Eurocontrol, URL <https://www.eurocontrol.int/publication/european-airline-delay-cost-reference-values>.
- Doctor, F., Budd, T., Williams, P.D., Prescott, M., Iqbal, R., 2022. Modelling the effect of electric aircraft on airport operations and infrastructure. *Technol. Forecast. Soc. Change* 177, 121553. <http://dx.doi.org/10.1016/j.techfore.2022.121553>.
- Eviation, 2022. Alice. Eviation. URL <https://www.eviation.com/aircraft/>.

- Flightradar24, 2022. Wideroe routes and destinations. Flightradar24. URL <https://www.flightradar24.com/data/airlines/wf-wif/routes>.
- Garrow, L.A., German, B.J., Leonard, C.E., 2021. Urban air mobility: A comprehensive review and comparative analysis with autonomous and electric ground transportation for informing future research. *Transp. Res. C* 132, 103377. <http://dx.doi.org/10.1016/j.trc.2021.103377>.
- Guo, Z., Zhang, X., Balta-Ozkan, N., Luk, P., 2020. Aviation to grid : Airport charging infrastructure for electric aircraft. In: Volume 10: Sustainable Energy Solutions for Changing the World: Part II. <http://dx.doi.org/10.46855/energy-proceedings-7180>.
- Guo, R., Zhang, Y., Wang, Q., 2014. Comparison of emerging ground propulsion systems for electrified aircraft taxi operations. *Transp. Res. C* 44, 98–109. <http://dx.doi.org/10.1016/j.trc.2014.03.006>.
- Hepperle, M., 2012. Electric Flight - Potential and Limitations. Lisbon, Portugal, URL <https://elib.dlr.de/78726/1/MP-AVT-209-09.pdf>.
- Holland, F., 2021. DHL express buys electric cargo planes for U.S. package delivery from start-up eviation. CNBC News. URL <https://www.cnbc.com/2021/08/03/dhl-express-buys-eviation-electric-planes-for-us-package-delivery.html>.
- Justin, C.Y., Payan, A.P., Briceno, S.I., German, B.J., Mavris, D.N., 2020. Power optimized battery swap and recharge strategies for electric aircraft operations. *Transp. Res. C* 115, 102605. <http://dx.doi.org/10.1016/j.trc.2020.02.027>.
- Justin, C.Y., Payan, A.P., Mavris, D.N., 2022. Integrated fleet assignment and scheduling for environmentally friendly electrified regional air mobility. *Transp. Res. C* 138, 103567. <http://dx.doi.org/10.1016/j.trc.2022.103567>.
- Klesty, V., 2022. Electric cars hit 65% of Norway sales as Tesla grabs overall pole. Reuters. URL <https://www.reuters.com/business/autos-transportation/electric-cars-take-two-thirds-norway-car-market-led-by-tesla-2022-01-03/>.
- Kwizera, O., Nurre, S.G., 2018. Using drones for delivery: A two-level integrated inventory problem with battery degradation and swap stations. In: *Proceedings of the Industrial and Systems Engineering Research Conferences*. pp. 1–6.
- Liu, W., Niu, S., Xu, H., Li, X., 2016. A new method to plan the capacity and location of battery swapping station for electric vehicle considering demand side management. *Sustainability* 8 (6), 557. <http://dx.doi.org/10.3390/su8060557>, Number: 6 Publisher: Multidisciplinary Digital Publishing Institute.
- Mak, H.-Y., Rong, Y., Shen, Z.-J.M., 2013. Infrastructure planning for electric vehicles with battery swapping. *Manage. Sci.* 59 (7), 1557–1575. <http://dx.doi.org/10.1287/mnsc.1120.1672>, Publisher: INFORMS.
- Mitici, M., Pereira, M., Oliviero, F., 2022. Electric flight scheduling with battery-charging and battery-swapping opportunities. *EURO J. Transp. Logist.* 11, 100074. <http://dx.doi.org/10.1016/j.ejtl.2022.100074>.
- Muralidharan, N., Self, E.C., Dixit, M., Du, Z., Essehli, R., Amin, R., Nanda, J., Belharouak, I., 2022. Next-generation cobalt-free cathodes – A prospective solution to the battery industry’s cobalt problem. *Adv. Energy Mater.* 12 (9), 2103050. <http://dx.doi.org/10.1002/aenm.202103050>, eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/aenm.202103050>.
- Nordpool Group, 2022. Hourly electricity prices. URL <https://www.nordpoolgroup.com/en/Market-data1/Dayahead/Area-Prices/ALL1/Hourly/>.
- Nurre, S.G., Bent, R., Pan, F., Sharkey, T.C., 2014. Managing operations of plug-in hybrid electric vehicle (PHEV) exchange stations for use with a smart grid. *Energy Policy* 67, 364–377. <http://dx.doi.org/10.1016/j.enpol.2013.11.052>.
- Olje- og energidepartementet, 2016. Renewable energy production in Norway. Government.no, Publisher: regjeringen.no. URL <https://www.regjeringen.no/en/topics/energy/renewable-energy/renewable-energy-production-in-norway/id2343462/>.
- Paoli, L., Dasgupta, A., McBain, S., 2022. International Energy Agency : Electric Vehicles. Tech. Rep., International Energy Agency, URL <https://www.iea.org/reports/electric-vehicles>.
- Park, S., Zhang, L., Chakraborty, S., 2017. Battery assignment and scheduling for drone delivery businesses. In: 2017 IEEE /ACM International Symposium on Low Power Electronics and Design. ISLPED, pp. 1–6. <http://dx.doi.org/10.1109/ISLPED.2017.8009165>.
- Salucci, F., Trainelli, L., Faranda, R., Longo, M., 2019. An optimization model for airport infrastructures in support to electric aircraft. In: 2019 IEEE Milan PowerTech. pp. 1–5. <http://dx.doi.org/10.1109/PTC.2019.8810713>.
- Sarker, M.R., Pandžić, H., Ortega-Vazquez, M.A., 2015. Optimal operation and services scheduling for an electric vehicle battery swapping station. *IEEE Trans. Power Syst.* 30 (2), 901–910. <http://dx.doi.org/10.1109/TPWRS.2014.2331560>, Conference Name: IEEE Transactions on Power Systems.
- Schneider, F., Thonemann, U.W., Klabjan, D., 2018. Optimization of battery charging and purchasing at electric vehicle battery swap stations. *Transp. Sci.* 52 (5), 1211–1234. <http://dx.doi.org/10.1287/trsc.2017.0781>, Publisher: INFORMS.
- sentralbyrå, S., 2022. Electricity prices. Statistisk sentralbyrå. URL <https://www.ssb.no/en/energi-og-industri/energi/statistikk/elektrisitetspriser>.
- Shao, Q., Shao, M., Lu, Y., 2021. Terminal area control rules and eVTOL adaptive scheduling model for multi-vertiport system in urban air Mobility. *Transp. Res. C* 132, 103385. <http://dx.doi.org/10.1016/j.trc.2021.103385>.
- Soltani, M., Ahmadi, S., Akgunduz, A., Bhuiyan, N., 2020. An eco-friendly aircraft taxiing approach with collision and conflict avoidance. *Transp. Res. C* 121, 102872. <http://dx.doi.org/10.1016/j.trc.2020.102872>.
- Sultana, U., Khairuddin, A.B., Sultana, B., Rasheed, N., Qazi, S.H., Malik, N.R., 2018. Placement and sizing of multiple distributed generation and battery swapping stations using grasshopper optimizer algorithm. *Energy* 165, 408–421. <http://dx.doi.org/10.1016/j.energy.2018.09.083>.
- Sun, B., Sun, X., Tsang, D.H.K., Whitt, W., 2019. Optimal battery purchasing and charging strategy at electric vehicle battery swap stations. *European J. Oper. Res.* 279 (2), 524–539. <http://dx.doi.org/10.1016/j.ejor.2019.06.019>.
- Sun, B., Tan, X., Tsang, D.H.K., 2018. Optimal charging operation of battery swapping and charging stations with QoS guarantee. *IEEE Trans. Smart Grid* 9 (5), 4689–4701. <http://dx.doi.org/10.1109/TSG.2017.2666815>, Conference Name: IEEE Transactions on Smart Grid.
- Taraldsen, L.E., 2021. Norway’s Wideroe to Fly First Zero-Emission Passenger Plane, Europe ed. Bloomberg, URL <https://www.bloomberg.com/news/articles/2021-11-10/norway-s-wideroe-plans-first-zero-emission-plane-in-five-years>.
- Taylor-Marriott, N., 2022. American cape air orders 75 electric airplanes from eviation. Simple Flying. URL <https://simpleflying.com/eviation-announces-75-plane-order-from-cape-air-for-electric-plane/>.
- Trainelli, L., Salucci, F., Riboldi, C.E.D., Rolando, A., Bigoni, F., 2021. Optimal sizing and operation of airport infrastructures in support of electric-powered aviation. *Aerospace* 8 (2), 40. <http://dx.doi.org/10.3390/aerospace8020040>.
- UNFCCC, 2021. International Aviation Climate Ambition Coalition - COP 26 Declaration. United Nations, URL <https://ukcop26.org/cop-26-declaration-international-aviation-climate-ambition-coalition/>.
- Worley, O., Klabjan, D., 2011. Optimization of battery charging and purchasing at electric vehicle battery swap stations. In: 2011 IEEE Vehicle Power and Propulsion Conference. (ISSN: 1938-8756) pp. 1–4. <http://dx.doi.org/10.1109/VPPC.2011.6043182>.
- Wu, H., Pang, G.K.-H., Choy, K.L., Lam, H.Y., 2017. A charging-scheme decision model for electric vehicle battery swapping station using varied population evolutionary algorithms. *Appl. Soft Comput.* 61, 905–920. <http://dx.doi.org/10.1016/j.asoc.2017.09.008>.
- Zhan, W., Wang, Z., Zhang, L., Liu, P., Cui, D., Dorrell, D.G., 2022. A review of siting, sizing, optimal scheduling, and cost-benefit analysis for battery swapping stations. *Energy* 258, 124723. <http://dx.doi.org/10.1016/j.energy.2022.124723>.
- Ziegler, M., Trancik, J., 2021. Re-examining rates of lithium-ion battery technology improvement and cost decline. *Energy Environ. Sci.* 14 (4), 1635–1651. <http://dx.doi.org/10.1039/DOE02681F>, Publisher: Royal Society of Chemistry.