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AIRPORT INFRASTRUCTURE SIZING FOR A REGIONAL ELECTRIC AVIATION NETWORK

Finn Vehlhaber[1] & Mauro Salazar[1]

[1]Control Systems Technology section, Department of Mechanical Engineering, Eindhoven University of Technology, 5600 MB Eindhoven, The Netherlands {f.n.vehlhaber, m.r.u.salazar}@tue.nl

Abstract

Electric aircraft will soon be introduced to regional markets and airport operators will need to provide the necessary charging infrastructure to enable their operations. Most regional airports lack the grid connection to support fleet charging and a recent push to reduce emissions in the energy mix that sees national power grids struggling calls for a grid-independent and sustainable solution for these airports. This paper introduces a framework for the sizing of a system for on-site energy generation and storage in support of electric flight operations for a regional aviation network. Specifically, it shows how the properties of the flight network can be leveraged for the strategic sizing of the electric infrastructure for a case study on the Dutch Leeward Antilles, highlighting airport specific requirements that arise from considering the air transport and energy system as a whole. Results with rough cost estimations for the infrastructure components show that installing energy and charging infrastructure at every airport in the flight network leads to a marginal cost decrease compared to a selective strategy where infrastructure is only installed at few airports. This latter case is also shown to have repercussions on infrastructure decisions on every other airport in the network. On the other hand, adapting the battery size of the aircraft in the fleet to the flight network requirements can lead to a significant decrease of up to 17 % in total infrastructure costs.

Keywords: Electric Aviation, Flight Operations, Infrastructure Sizing, Aircraft Routing Problem

1. Introduction

As more manufacturers are introducing mature prototypes, it is only a matter of time until electric aircraft become attainable. Owing to current limitations in battery technology, these first models will find use cases in commuter networks and connecting remote communities where they would replace small fossil-fuel-powered airplanes. This development is poised to contribute to carbon neutral aviation, which the IATA is committed to reaching in 2050 [1].

However, a crucial requirement for a widespread implementation of electric aircraft is the existence of charging infrastructure on the ground. Airports need to be prepared for the advent of electric aviation, which comes with a number of challenges. Among these, commuter airports often lack the grid connection to supply the vast amounts of power required to charge electric aircraft. This problem is perpetuated by the issues with strained power grids that many countries already face in the wake of the energy transition. Many airports already make use of solar power on their large premises to facilitate sustainable operations and grid independence, which could be expanded upon in the future, with the implementation of battery energy storage systems (BESS) and energy management schemes. Still, airport and fleet operators alike lack insights on how to size this infrastructure and how electric aviation will impact their operations. In addition, the inherent connection between flight operations and the local power availability, comprising a joint air transport and power network, cannot be overlooked.

Against this backdrop, this paper provides an optimization framework to size the energy infrastructure at all airports within an electric air mobility network given an existing flight schedule, specifically aiming at a grid independent operation.

Related Literature This paper is related to two streams of research, namely electric aircraft operations and infrastructure sizing. The introduction of electric aircraft will not majorly disrupt airport operations, given a strategic planning of the infrastructure, as Doctor et al. investigated using Discrete Event Simulation (DES) [2]. Nevertheless, it will have a significant impact on the power requirements of the respective airports. Therefore, Justin et al. devise battery swap and recharge strategies to support electric aviation and show that optimizing the charge schedules for electric aircraft can be beneficial for both operation and infrastructure, as they alleviate strain on the power grid and reduce capital expenditure [3]. For the requirements of said infrastructure, several authors have taken mixed-integer linear programming (MILP) approaches, to obtain the size of the charging system at an airport that hosts electric planes [4, 5]. Strategic aircraft to flight assignment has been researched extensively to increase airline profits [6], also in combination with adaptation of the cruise speed to reduce fuel consumption [7]. Mitici et al. leverage these concepts from the aircraft routing problem (ARP) to assign aircraft to flights and thus size both fleet and infrastructure simultaneously for the lowest investment costs [8]. The aforementioned authors collectively assume a given schedule and the electric power to be provided by the local power grid, whereas van Amstel implements renewable energy into his sizing framework [9]. Additionally, he allows for slight flight delays for a more beneficial recharging strategy, and sizes the charging infrastructure for a representative peak day, as well as the renewable energy system for a year of operations.
However, thus far most authors have merely considered a single airport and have ignored the connective properties and their implications on the charging infrastructure on each airport within a regional aviation network. Alternatively, other researchers tackle the network design problem for electric aviation, minimizing carbon content in the energy mix [10] or maximizing connectivity [11], the latter also being concerned with the best selection of airports as charging bases in an attempt to reduce installation costs. This idea of a connected air transport-energy network is furthered in a subsequent work, where Kinene and Birolini formulate a large scale time-space-energy problem, with which they design a subsidized electrified air transport network that meets passenger demand while reducing investment costs through a strategic choice of airports, fleet assignment, flight schedules, and charging infrastructure size [12]. In a similar context, Oosterom and Mitici investigate the infrastructure necessary for aircraft battery swapping [13], whereby they employ a recourse for more representative results. Neither of these authors explicitly account for grid independent operation.
In conclusion, the sizing of electric infrastructure for aviation has been explored for single airports, also with the inclusion of renewable energy, but a detailed sizing of the battery storage system and renewable energy sources for grid independent operation considering the complete regional flight network has not yet been pursued.

Statement of Contributions In this paper, we introduce a framework for the sizing of grid-independent electric airports that constitute a network in which electric aviation is to be established. In particular, we account for local constraints of each airport individually, while also accounting for the fact that these airports together form an electric power and transport network.

2. Methodology

In this section, we introduce the optimization framework with which we can jointly size the airport infrastructure and aircraft fleet for a given flight schedule and solar radiation data. To this end, we outline the necessary constraints and describe the energy model used for the airports.

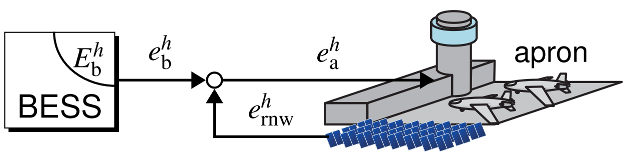

Figure 1 – Energy model of an airport $h \in \mathcal{H}$ with renewable energy sources in addition to the grid connection and a stationary battery (BESS). Arrows indicate positive direction of power flow.

Table 1 – Nomenclature

Sets and Indices

$\mathcal{H}$	airports in the network, indexed by h
$\mathcal{T}$	time intervals within a day, indexed by k
$\mathcal{W}$	set of days in the week, indexed by d
$\mathcal{F}$	flights in the week, indexed by i
$\mathcal{F}_d$	$\subset \mathcal{F}$, flights in day d
$\mathcal{A}_i$	$\subset \mathcal{F}^d$, potential immediate successors of i
$\mathcal{B}_i$	$\subset \mathcal{F}^d$, pot. immediate predecessors of i

Parameters

o_i, d_i	origin and destination airport of i
t_i	departure time of flight i
$t_{\mathrm{f},i}$	time of flight for i: $t_{\mathrm{f},i} \in \Delta_i^{\mathrm{t}}$
$E_{\mathrm{f},i}$	energy required for i: $E_{\mathrm{f},i} \in \Delta_i^{\mathrm{E}}$
$\mathbf{G}^h$	time series for the solar irradiance at h where $\mathbf{G}^h = (G^h(t) : t \in [0, t^{\lvert\mathcal{T}\rvert}])$
c_κ	unit installation cost for variable κ

Decision Variables

x_i	$\begin{cases} 1, & \text{if } i \text{ is a first flight of the day,} \\ 0, & \text{otherwise.} \end{cases}$
y_{ij}	$\begin{cases} 1, & \text{if } i \text{ follows } j \text{ immediately on a day,} \\ 0, & \text{otherwise.} \end{cases}$
z_i	$\begin{cases} 1, & \text{if } i \text{ is a last flight of the day,} \\ 0, & \text{otherwise.} \end{cases}$
w_h^d	number of planes staying at an airport h on day d
E_i	state of energy of the aircraft assigned to i at departure
e_i^k	energy recharged after i during k
$E_{\mathrm{b,max}}^h$	maximum capacity of the BESS at h
A_{sp}^h	area of the solar cells at h
q^h	$\begin{cases} 1, & \text{if infrastructure installed at } h, \\ 0, & \text{otherwise.} \end{cases}$

2.1 Electric Aircraft Routing Problem

For the intended application we reduce the fleet assignment problem [7, 8] to a sequencing problem we denote as electric aircraft routing problem (eARP). We adopt the nomenclature stated in Table 1, with binary decision variables x_i and z_i that are non-zero if flight i is the first or last flight of an aircraft, respectively, and y_{ij}, which is non-zero if flights i and j are assigned to the same aircraft as consecutive flights. All flights are included in the set $\mathcal{F}$, where each flight i is characterized by its departure time t_i, origin and destination airports o_i and d_i, and a time of flight $t_{\mathrm{f},i}$ as well as the energy expended $E_{\mathrm{f},i}$. From this exogenous information we can construct sets $\mathcal{A}_i$ and $\mathcal{B}_i$ that for each flight contain all flights that can be executed by the same aircraft directly after and before, respectively. The flight demand is served by a homogeneous fleet of electric aircraft.

With these on hand, we introduce the binary constraints for the eARP as

$$x_i + \sum_{j \in \mathcal{B}_i} y_{ji} - z_i - \sum_{j \in \mathcal{A}_i} y_{ij} = 0 \quad \forall i \in \mathcal{F}_d \quad \forall d \in \mathcal{W}, \tag{1}$$

$$x_i + \sum_{j \in \mathcal{B}_i} y_{ji} = 1 \quad \forall i \in \mathcal{F}_d \quad \forall d \in \mathcal{W}, \tag{2}$$

$$\sum_{\substack{i \in \mathcal{F}^d: \\ d_i = h}} z_i + w_h^d = \sum_{\substack{i \in \mathcal{F}^{d+1}: \\ o_i = h}} x_i + w_h^{d+1} \quad \forall h \in \mathcal{H} \quad \forall d \in \{1, \dots, |\mathcal{W}| - 1\}, \tag{3}$$

$$\sum_{\substack{i \in \mathcal{F}^{|\mathcal{W}|}: \\ d_i = h}} z_i + w_h^{|\mathcal{W}|} = \sum_{\substack{i \in \mathcal{F}^1: \\ o_i = h}} x_i + w_h^1 \quad \forall h \in \mathcal{H}. \tag{4}$$

Here, (1) and (2) ensure continuity and full coverage of the flight schedule, while (3) and (4) are conservation constraints that enforce the same amount of planes at an airport at the end of one day and the beginning of the next.

Next, we include energy constraints to ensure feasible flight sequencing. First, we establish a connection between the state of energy of the battery at the beginning of a flight through

$$E_j - E_i + E_{\mathrm{f},i} - \sum_{k \in \mathcal{T}} e_i^k \geq (y_{ij} - 1) \cdot \overline{E} \qquad \forall i, j : j \in \mathcal{A}_i, \tag{5}$$

$$E_j - E_i + E_{\mathrm{f},i} - \sum_{k \in \mathcal{T}} e_i^k \leq (1 - y_{ij}) \cdot \overline{E} \qquad \forall i, j : j \in \mathcal{A}_i, \tag{6}$$

where $\overline{E}$ is a very large number [14]. The state of energy is subject to the limits

$$E_i \in [E_{\min} + E_{\mathrm{f},i}, E_{\max}] \quad \forall i \in \mathcal{F}, \tag{7}$$

where $E_{\max}$ and $E_{\min}$ are the maximum and minimum state of energy of the aircraft battery, respectively, on the assumption of a homogeneous fleet. Before the first flight of the day, the aircraft must be fully charged, i.e.,

$$E_i \geq E_{\max} - (1 - x_i) \cdot \overline{E} \,, \tag{8}$$

and after the last flight of the day the aircraft must be recharged to full state of energy, which we implement through

$$E_i - E_{\mathrm{f},i} + \sum_{k \in \mathcal{T}} e_i^k \geq E_{\max} - (1 - z_i) \cdot \overline{E} \,, \tag{9}$$

$$E_i - E_{\mathrm{f},i} + \sum_{k \in \mathcal{T}} e_i^k \leq E_{\max} + (1 - z_i) \cdot \overline{E} \,. \tag{10}$$

Finally, we introduce constraints on the energy recharged after a flight, fo which we split the period of operations into time steps of equal length Δt that make up the set $\mathcal{T}$ and have a start time t^k. For each flight, we define as decision variables the portion of energy recharged during each time step after the flight, e_i^k. Hereby, it holds that

$$\sum_{k \in \mathcal{T}} e_i^k \leq P_{\mathrm{c,max}} \cdot (t_j - t_i - t_{\mathrm{f},i}) + (1 - y_{ij}) \cdot \overline{E} \qquad \forall i, j \in \mathcal{F} : j \in \mathcal{A}_i, \tag{11}$$

$$e_i^k \in [0, \Delta t \cdot P_{\mathrm{c,max}}] \qquad \forall k \in \mathcal{T} \quad \forall i \in \mathcal{F} \,, \tag{12}$$

$$e_i^k = 0 \qquad \forall k \in \mathcal{T} : t^k < t_i + t_{\mathrm{f},i} \quad \forall i \in \mathcal{F} \,, \tag{13}$$

$$e_i^k \leq (t^{k+1} - t_i - t_{\mathrm{f},i}) \cdot P_{\mathrm{c,max},i} \qquad \forall k \in \mathcal{T} : t_i + t_{\mathrm{f},i} \in [t^k, t^{k+1}] \quad \forall i \in \mathcal{F} \,, \tag{14}$$

$$e_i^k \leq (\Delta t - t^{k+1} + t_j) \cdot P_{\mathrm{c,max},i} + (1 - y_{ij}) \cdot \overline{E} \qquad \forall k \in \mathcal{T} : t_j \in [t^k, t^{k+1}], \forall i, j \in \mathcal{F} : j \in \mathcal{A}_i \,, \tag{15}$$

$$e_i^k \leq (1 - y_{ij}) \cdot \overline{E} \qquad \forall k \in \mathcal{T} : t^{k+1} \geq t_j, \forall i, j \in \mathcal{F} : j \in \mathcal{A}_i \,. \tag{16}$$

Above, the total energy recharged after a flight is limited by the time an aircraft is present on the apron (11). The energy recharged per time step is always non-negative and smaller than the maximum amount possible (12), and an aircraft cannot be charged after a flight if that flight has not yet landed (13). Additionally, the energy recharged in the time step in which the aircraft lands after a flight cannot exceed the maximum energy that can be recharged between the arrival time and the end of that time step (14). Finally, the energy recharged in the time step at which the aircraft departs on its next flight after i is limited by the time window between the start time of that time step and the departure time (15), and it must be zero for all time steps following that one (16).

Energy Infrastructure

Aircraft can recharge at airports after a flight if required, provided that the airport has the necessary infrastructure installed. In our sizing problem, this infrastructure is not required at every airport in the network, in fact, it could even be impossible that it exists at certain airports if prohibited by local circumstances. In the following, to evaluate the infrastructure requirements at every airport, we first introduce the model that we assume for every airport.

We capture the existence of charging infrastructure through a binary decision variable q^h that is non-zero if airport h has chargers on the apron. Hence, the energy recharged after a flight is subject to the constraint

$$\sum_{k \in \mathcal{T}} e_i^k \leq \sum_{h : h = d_i} q^h \cdot \overline{E} \quad \forall i \in \mathcal{F} . \tag{17}$$

The energy system at an airport consists of an array of solar cells, the area $A_{\mathrm{sp}}^h \geq 0$ of which is a decision variable for each airport $h \in \mathcal{H}$. The solar power obtained can be used to charge aircraft at the apron. An energy buffer is installed at each airport in the form of a battery energy storage system (BESS), with its size $E_{\mathrm{BESS}}^h \geq 0$ to be obtained through the optimization problem. At each airport we define

$$e_{\mathrm{rnw}}^k = A_{\mathrm{sp}}^h \cdot \eta_{\mathrm{sp}} \cdot \int_{t^k}^{t^{k+1}} G^h(\tau) \, \mathrm{d}\tau, \tag{18}$$

$$e_{\mathrm{a}}^k = \sum_{i : d_i = h} e_i^k, \tag{19}$$

as the energy gained from renewables and the energy drawn on the apron, respectively, and η_b is the charging efficiency of the battery, and $G^h(\tau)$ is the solar irradiance per time at the airport, which is an exogenous input. The energy balance is stated as follows:

$$e^k_\mathrm{b} = e^k_\mathrm{rnw} - e^k_\mathrm{a}, \tag{20}$$

where e^k_b is the energy drawn from the battery during the time step. The battery dynamics are defined as

$$E^{h,k+1}_\mathrm{b} \leq E^{h,k}_\mathrm{b} - \eta_\mathrm{b} \cdot e^k_\mathrm{b} \quad \forall k \in \mathcal{T}, \forall h \in \mathcal{H}, \tag{21}$$

$$E^{h,k+1}_\mathrm{b} \leq E^{h,k}_\mathrm{b} - \frac{1}{\eta_\mathrm{b}} \cdot e^k_\mathrm{b} \quad \forall k \in \mathcal{T}, \forall h \in \mathcal{H}, \tag{22}$$

where $E^{h,k}_\mathrm{b}$ is the state of energy in the BESS at the beginning of that time step and (21) models the internal losses during charging (i.e., when e^k_b is positive), while (22) is the equivalent for discharging. We further assume that the BESS is only used to support flight operations and the airport is grid-independent. The state of energy in the BESS is subject to the limits

$$E^{h,k}_\mathrm{b} \in \left[\xi_\mathrm{b,min} \cdot E^h_\mathrm{BESS}, E^h_\mathrm{BESS}\right] \quad \forall k \in \mathcal{T} \quad \forall h \in \mathcal{H}\,. \tag{23}$$

Additionally, the size of the BESS governs the maximum output power of the battery, namely through the permissible charging rate r^h_c which is defined as the fraction of the maximum battery capacity that can be charged within one hour. Hence,

$$e^k_\mathrm{b} \in \left[-E^h_\mathrm{BESS} \cdot r^h_\mathrm{c}, E^h_\mathrm{BESS} \cdot r^h_\mathrm{c}\right] \quad \forall k \in \mathcal{T} \quad \forall h \in \mathcal{H}. \tag{24}$$

Optimization Problem

With the constraints defined we can now formulate the optimization problem,which aims to minimize the installation costs for the infrastructure necessary to operate an electric flight network, where we have obtained the costs c_sp, c_BESS, c_ch, and c_ac for the solar cells, BESS, charging infrastructure, and aircraft acquisition from the literature (e.g. [9, 15]).

Problem 1 (Aircraft Routing and Fleet and Infrastructure Sizing Problem)**.** *The optimal fleet and electric infrastructure size at each airport in the electric air transport network is obtained from the solution of*

$$\min_{\substack{\{A^h_\mathrm{sp}, E^h_\mathrm{BESS}, q^h\}_{h\in\mathcal{H}},\\ \left\{\{e^k_i\}_{k\in\mathcal{T}}, x_i, \{y_{ij}\}_{j\in\mathcal{A}_i}, z_i\right\}_{i\in\mathcal{F}}}} \sum_{h\in\mathcal{H}} \left(A^h_\mathrm{sp} \cdot c_\mathrm{sp} + E^h_\mathrm{BESS} \cdot c_\mathrm{BESS} + q^h \cdot c_\mathrm{ch}\right) + \left(\sum_{i\in\mathcal{F}^1} x_i + \sum_{h\in\mathcal{H}} w^1_h\right) \cdot c_\mathrm{ac}$$

$$\text{s.t.} \quad \begin{array}{ll} (1)-(4) & \textit{Scheduling Constraints,} \\ (5)-(16) & \textit{Aircraft Constraints,} \\ (17)-(24) & \textit{Infrastructure Constraints.} \end{array}$$

3. Results

In this section, we apply the sizing framework in a case study for a regional flight network in the Dutch Leeward Antilles (ABC islands) and comment on it.

The ABC islands are served by frequent inter-island commuter traffic with small airplanes [16], that could be replaced with small electric aircraft such as Eviation's Alice in the near future [17]. Thus, we envision a scenario where the current fleet of three 9-seater aircraft is completely replaced by the electric alternative. To estimate the electric energy required for a flight, we follow a procedure inspired by [18] and outlined in [19] which uses altitude and velocity profiles of real flights between these islands, courtesy of flightradar24.com [16]. For the solar irradiation, we take the average of real data for the islands during the month of August 2023 [20].

We parse Problem 1 with YALMIP [21] in MATLAB and solve it using Gurobi [22] with a time step $\Delta t =$ 30 min. Depending on the scenario, the problem is solved within a few hours on a machine using 128 cores, which, although arguably being an acceptable time for an off-line sizing problem, will be subject to further comments below.
The sizing results are reported in Table 2 on the far left, with Fig. 2 showing the evolution of the state of charge at each airport and the flight assignments for the aircraft.
In the results for the network optimal case (i) we notice a discrepancy in size for the energy systems at the respective airports, namely that the BESS and solar panel array at Curaçao is larger than those at the other airports in the network. This can be explained by the fact that this island serves as the base of the fleet and is either the origin or destination of every flight, but we notice that installing charging infrastructure at the other destinations is nevertheless beneficial for the network operation. First, as seen in Fig. 2 at the top, flights to Aruba are rare and the aircraft assigned to them stays at Aruba until the evening, so it is sensible to charge it there to reduce the energy required at Curaçao in the evening, when solar energy is no longer available and the aircraft need to be charged from the BESS. Second, the existence of a BESS at Aruba reduces the required amount of solar cells, as the BESS can be charged on days with no flights to then supply energy during the beginning of the week. This can be clearly seen by the dip in the state of charge of the BESS in the middle of the week. A similar phenomenon occurs at Bonaire, albeit less pronounced. Here, the planes have such short turnaround times, that often the BESS is needed to supply additional energy to quickly charge the planes when the solar power alone does not suffice.

3.1 Comparison of different infrastructure installation strategies

Different airports are not usually operated by the same company, so some airport operators may be more eager than others to install charging infrastructure in the early years of electric aviation, which begs the question as to what extent this would impact the aircraft operation and overall installation costs in the network. Therefore, we explore options (ii), where charging infrastructure and the renewable energy system are not installed at Aruba, and (iii) where charging is only possible at Curaçao, by imposing constraints on q^h. A comparison of these results is reported in Table 2 on the left, providing insights into possible installation strategies.
Comparing the three scenarios, we find that restricting the installation of infrastructure at some airports in the network increases overall installation costs as the necessary total amount of solar panels and stationary battery modules would increase. Interestingly, between scenarios (i) and (ii) as compared in Fig. 2, we now find that the optimal size of the solar array at Bonaire has decreased, as more charging—also of those aircraft going to Bonaire—has shifted to Curaçao. Fig. 3 shows this trend where on most days the energy recharged at Bonaire decreases compared to case (i). Also, the BESS at Bonaire is filled up towards the end of the week to accommodate the increase in flights early in the following week, a phenomenon previously exhibited at Aruba.

Table 2 – Infrastructure and Fleet sizing results for different scenarios for the Flight Network on the ABC Islands. "Optimal" refers to the respective network optimal case.

	nominal aircraft configuration						**smaller aircraft battery**			
	optimal (i)		not at AUA (ii)		CUR only (iii)		450 kWh (iv)		600 kWh (v)	
Location	E_{BESS} (MWh)	A_{sp} (ha)	E_{BESS} (MWh)	A_{sp} (ha)	E_{BESS} (MWh)	A_{sp} (ha)	E_{BESS} (MWh)	A_{sp} (ha)	E_{BESS} (MWh)	A_{sp} (ha)
Aruba (AUA)	0.92	1.56	0	0	0	0	0.51	0.90	0.65	1.15
Bonaire (BON)	1.09	3.39	1.39	2.81	0	0	1.12	2.49	1.21	2.78
Curaçao (CUR)	1.54	5.99	2.35	8.33	3.81	11.35	1.30	5.65	1.40	5.68
total	3.55	10.94	3.74	11.14	3.81	11.35	2.93	9.04	3.26	9.61
fleet size	3		3		3		3		3	
cost w.r.t. (i)										
total	+ 0 %		+1.42 %		+2.87 %		-13.12 %		-9.08 %	
infra. only	+ 0 %		+1.87 %		+3.79 %		-17.31 %		-11.98 %	

In general, the reliance on the BESS as an energy buffer becomes more prominent, as on most days the amount of energy recharged from the battery increases except for the two last days of the week, where solar power is used instead, directly, as the BESS is charged for the uptick in flights at the beginning of the next week. In fact, the BESS capacity at Curaçao increases by more than 50 % compared to the network optimal case (i). The increase in total solar cell area can be explained by the heavier reliance on the BESS too, as energy buffering introduces conversion losses.
Finally, restricting the charging infrastructure to Curaçao leads to a further increase in total costs as expected. Across all three scenarios, however, the increase in costs is marginal and the fleet size is not affected. Therefore, operational reasons or other local constraints may prevail over pure installation costs.

3.2 Comparison of different aircraft battery sizes

The energy required for the flights in the network considered here is much less than the battery capacity of the aircraft, and it can be noted that the aircraft's state of charge rarely drops below half, and that only if multiple flights are flown in sequence without much charging in between. Since the battery contributes significantly to the weight of the aircraft, using a smaller battery would reduce the energy consumption and could potentially have a higher impact on infrastructure and operational decisions than local infrastructure constraints. We consider two additional scenarios where, instead of imposing constraints on the infrastructure, we reduce the battery capacity of the aircraft by half and one third, whilst keeping the same airframe. The results of these studies are reported in Table 2 on the right and show a clear reduction in infrastructure costs given the same assumed price for the aircraft as for the initial configuration. In both cases, the required fleet size does not increase compared to the normal aircraft configuration. Smaller battery capacities may also offer aerodynamic improvements to the aircraft, motivating further research in network-specific aircraft design as in [23]. Alternatively, one could envision aircraft designs with customizable battery sizes—potentially exchangeable as in [13]. For all cases considered in this study, the required BESS was in the same order of magnitude as the battery capacity of the aircraft, which enables potential second-life uses for their batteries as airports strive for grid-independence.

3.3 Discussion

Some comments on the limitations of the methodology and the problem structure are in order. First, we take the solar irradiation as given and deterministic, which simplifies our framework, but also yields an optimistic solution. Also, using weather data from other seasons may change the results significantly. Second, for our sizing problem we only assume one week of operations which, even when considering a peak week can skew the results. Third, the assumption of a homogeneous fleet may not be realistic, but can be easily changed in the future. A formulation of the presented framework for more representative periods of operations, also including probabilistic quantities for solar irradiation, flight duration and energy consumption, and even passenger volumes or different installation costs per airport is left for future work. Finally, the proposed methodology does not consider aircraft battery health, which may be compromised by frequent recharging and should be introduced to the framework in the future.
Due to the nature of the proposed problem formulation as a mixed-integer linear program (MILP) we may encounter computational issues with a larger amount of flights as Gürkan et al. point out [7]. Although not necessarily required for a sizing problem, we plan to address issues with computation time with case-specific alterations to the framework or heuristic approaches.

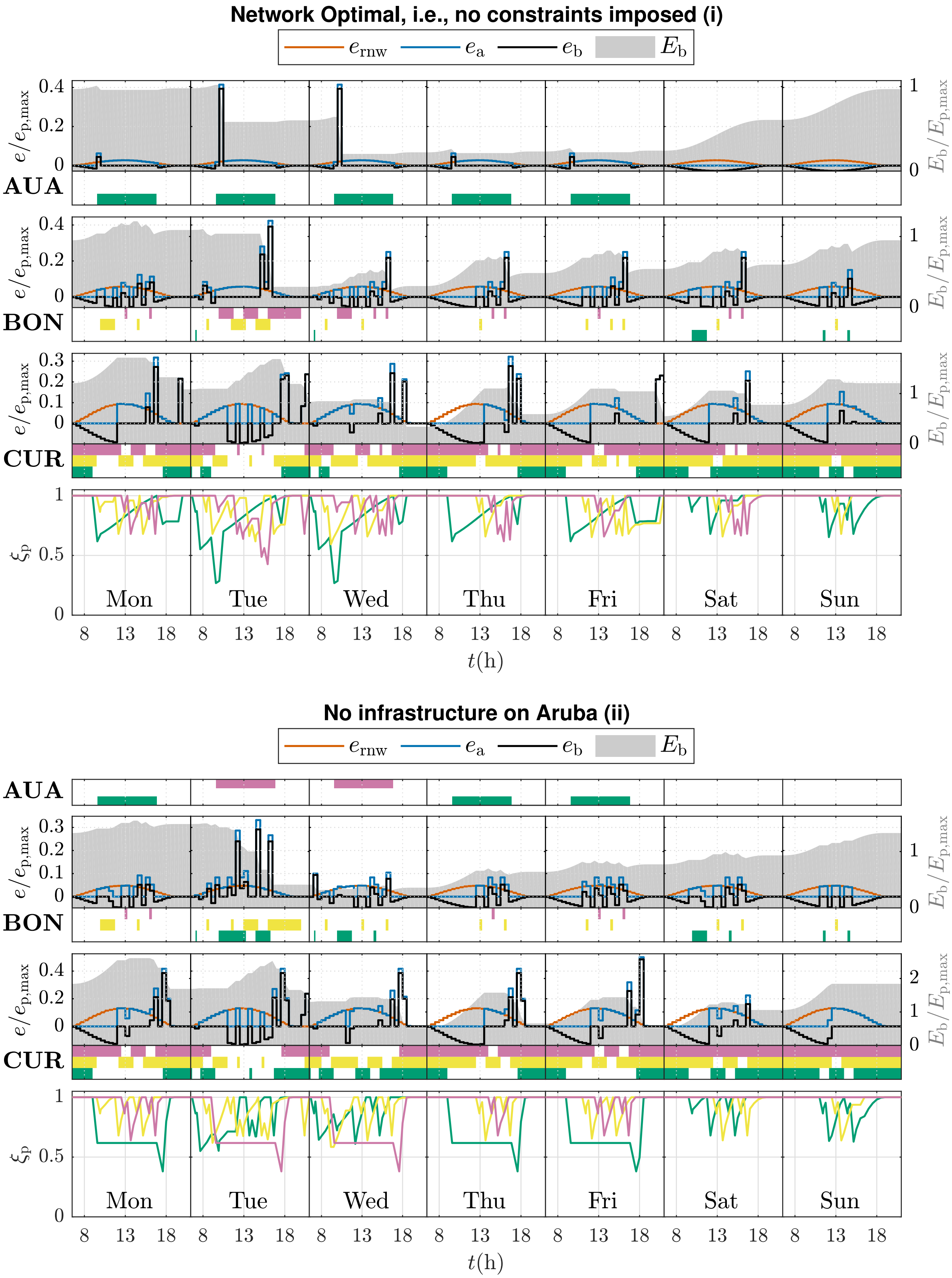

Figure 2 – Evolution of the state of charge of the BESS and all airplanes in the fleet, as well as the energy demands at every airport per time step normalized with the battery size of the Alice for a week of flight operations on the Dutch ABC islands for two selected scenarios.

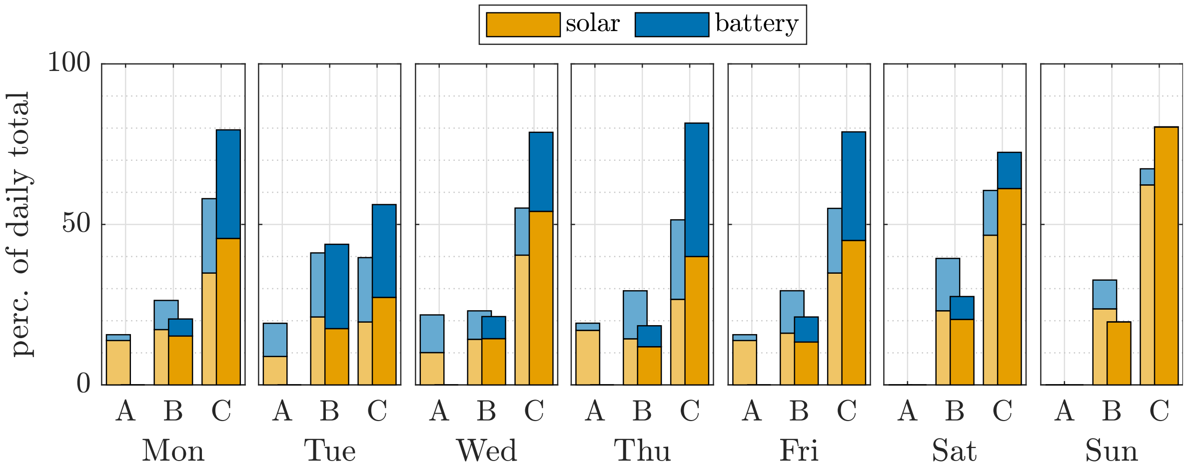

Figure 3 – Comparison of direct energy sources for aircraft charging for the network optimal scenario (i) (muted, background) and one with no charging infrastructure at Aruba (ii) for the flight network on the ABC Islands.

4. Conclusion

This paper introduced a framework for the sizing of the infrastructure necessary for the electrification of an existing aviation market. We applied the framework to a network of commuter flights on the Dutch ABC islands and gained insights on how the structure of the flight network influences the infrastructure requirements at each airport. Namely, for the case considered, we found that for an optimal operation every airport would have to have at least a minimal electric energy system installed, but to guarantee operations it would suffice to install this infrastructure at the base of the airline only, thus creating a simpler, albeit slightly more expensive, roll-out scenario to introduce electric aviation to the network. The results highlighted that decisions on the energy infrastructure of an airport and charge schedules and operations for the fleet are highly dependent on both network and aircraft type, and influence each other.

As future work we would like to explore a robust infrastructure sizing scheme with probabilistic inputs and for different scenarios, also considering battery aging and infrastructure amortization, as well as a sensitivity analysis of the results depending on the prices assumed for the infrastructure. In addition to that, the inclusion of a grid connection for demand response could be a compelling research direction, ultimately empowering airports to act as local energy hubs for their community. Finally, applying the framework in larger aviation networks in other areas of the world will provide further insights into the interdependence of infrastructure, operations, and fleet composition.

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5. Contact Author Email Address

Please address correspondence to Finn Vehlhaber at f.n.vehlhaber@tue.nl.

6. Copyright Statement

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