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Airport Readiness for Serving Electric Aircraft: Balancing Service Reliability and Power Demand

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Abstract

Electrification has significant potential to reduce aviation's carbon footprint. However, transitioning from conventional-fuel aircraft to battery-powered Electric Aircraft (EA) will impose infrastructure and energy requirements on airports. Airports are not currently prepared to support the high-frequency operations of EA, particularly for upcoming applications such as short-haul and flight training operations. Without adequate preparation, such operations risk compromising service levels and creating new peak electricity loads. This study develops a stochastic optimization framework for sizing airport infrastructure that jointly determines the optimal number of spare batteries and chargers, accounting for electrical grid capacity constraints and potential grid upgrades. Airport operations are modeled daily using real flight arrival and departure data, in which each arriving aircraft returns a battery with a given state of charge, and each departing aircraft requires a fully charged battery. System performance is evaluated using a Monte Carlo simulation that randomly samples independent daily operating scenarios from historical data. Reliability is defined as the probability that all departures within a day are served without battery shortages and with delays less than the acceptable delay time. A parallel-machine, non-preemptive scheduling MILP with power coupling and lateness and cost objectives — approximated via a greedy simulation-based heuristic. The objective function includes maximum lateness, total lateness over the horizon, costs for spare batteries and chargers, and the cost of upgrading grid capacity. The proposed approach quantifies trade-offs among battery inventory, charger capacity, and grid reinforcement and evaluates their impacts on reliability and peak power demand. The results demonstrate how incorporating grid upgrade costs can shift optimal infrastructure designs and provide decision-makers with a transparent tool for planning airport electrification under operational uncertainty and power constraints.

Keywords
Resource Optimization, Electric Vehicle Adoption, Power grid, Electric Vehicle Charging Infrastructure, Environmental Sustainability

1. Introduction

Using electric aircraft in high- and medium-traffic commercial aviation presents challenges in aircraft routing and charging due to limited battery technology. The need to charge the batteries during the short ground time after each flight, considering the available power at the airport, is one of them. Some solutions, such as high-power charging, may lead to battery aging and degradation, increased thermal management requirements, and significant energy consumption (Doctor et al. 2022; Lindberg and Leijon 2025). Infrastructural inadequacy, including insufficient grid availability across all flight networks, may also be considered an unaddressed challenge for fast charging in high-frequency commercial aviation (Justin et al. 2020). In addition, due to the high peak charging loads associated with electric aircraft, airports may incur high costs from peak electricity demand charges (Hou et al. 2024). According to (Doctor et al. 2022), despite the availability of high-power charging, the process can still take considerably longer than conventional refueling (e.g., 80–270 minutes for certain aircraft), which may increase turnaround times, contribute to airside congestion, and reduce effective stand capacity. Therefore, it is necessary to employ strategies that minimize and smooth peak power demand while still ensuring maximum energy delivery. A flattened power profile can be achieved by either integrating local energy storage systems, such as battery banks, or by using a battery-swapping technique to supply additional power during peak demand and store it during low-demand periods. In battery swapping, aircraft batteries are exchanged and recharged in a controlled manner, enabling a more continuous and lower-level power draw from the grid (Justin et al. 2020). Replacing the depleted battery with a previously charged one takes less time and better fits within the aircraft's turnaround time. The battery-swapping system offers additional operational and technical advantages. Since fully charged units are available before the arrival of the electric aircraft fleet, this reduces the risk of service disruptions and delay (Tang et al. 2026). Moreover, depleted batteries are recharged off-aircraft; the associated demand can be distributed more evenly over time or shifted to off-peak periods (Guo et al. 2023) to balance the electrical load pattern. The results of the study by (Justin et al. 2020) suggest that optimized battery swapping can reduce peak grid power demand by up to 61%. (Lindberg and Leijon 2025). Moreover, batteries stored at a battery swapping station (BSS) can function as a stationary energy storage system (ESS), enabling grid support by absorbing or supplying power in response to demand fluctuations (Guo et al. 2020). From a battery health perspective, slow charging rates and reduced thermal stress to extend battery longevity are also reported in the literature (Bigoni et al. 2018). Using battery swapping can bring economic advantages to the airlines and airport operators. Lower peak electricity prices and fewer battery replacements can reduce the operational cost (Bigoni et al. 2018; Guo et al. 2023). In addition, the "Aviation-to-Grid" (A2G) concept enables airports to utilize spare batteries to supply electricity back to the grid during periods of high demand, thereby creating an additional revenue stream (Guo et al. 2020; Justin et al. 2020).

A data-driven framework is offered in this study for designing airport battery-swap infrastructure under different seasonal traffic conditions. By combining stochastic modeling of flight schedules, energy demand, and operational disruptions with a multi-scenario analysis of low- and high-traffic periods, the approach which are inherent uncertainty in aviation operations. The model jointly optimizes essential infrastructure components—including chargers, spare batteries, and power capacity—while meeting reliability-based performance standards. Using Monte Carlo simulation and Pareto-based multi-objective analysis, the study finds designs that balance cost, capacity, and service reliability, preventing both under-sizing during peak demand and over-investment during normal operations. The rest of the paper is divided into 4 more sections. Section 2 reviews the academic research regarding airport operations and infrastructure design in the case of electric aircraft services. The employed methodology of the study is stated in the third section. Results and discussion, including the numerical assumptions and graphical results, are presented in the 4th part of the paper. The final section is the conclusion and future direction of the study.

1.1 Objectives
This study focuses on sizing airport infrastructure necessary for battery-swapping operations. The goal is to determine the optimal number of spare batteries and parallel chargers, considering grid power limitations and ensuring the required operational reliability under both low-traffic and high-traffic conditions. It aims to minimize system overdesign and under design. The evaluation uses real operational flight data and a Monte Carlo–driven simulation framework that captures the stochastic interactions between aircraft arrivals, departures, battery state of charge upon arrival, and potential charger failures. A robust Pareto front is constructed based on worst-case performance metrics such as maximum lateness, total lateness, and reliability. The final design is chosen from the feasible Pareto set to balance infrastructure costs with operational performance across multiple demand scenarios.

2. Literature Review
To fully leverage the benefits of battery swapping, the operation of swapping and recharging stations—particularly the scheduling of recharge activities—has been a central focus in the literature. The reviewed studies highlight several key distinctions in their approaches to battery-swapping scheduling, ranging from strategic infrastructure sizing to tactical real-time energy management and network-level fleet optimization. The objectives and goals of scheduling algorithms vary across research depending on the intended operational outcomes. Justin et al. (2020) specifically focus on reducing peak grid power demand. Their "power-optimized" strategy distributes charging activities over time to smooth the demand profile, achieving electricity cost reductions of up to 25%. They also try to reduce the overall capital and operating costs. Likewise, Trainelli et al. (2021) and Mitici et al. (2022) examine "power–investment" strategies that balance capital costs for spare batteries and chargers against ongoing electricity expenses. In another study by Tang et al. (2026), the electric and fuel aircraft scheduling optimization problem is addressed, aiming to coordinate a mixed fleet while minimizing the combined costs of emissions and flight delays. In different papers, different time horizons are used in the charging schedule process. Most other models, including those by Justin et al.

(2020) and Mitici et al. (2022), focus on deriving optimal schedules for a single day of operations under a fixed flight schedule. However, Oosterom & Mitici (2023) differentiate their work by adopting a two-stage recourse model that accounts for an entire year of operations. They demonstrate that optimizing based on a single peak or an average day, as done in earlier studies, can lead to suboptimal infrastructure sizing and scheduling decisions. Network-wise, some literature offers the scheduling solution at the hub level, assuming the battery swapping and charging takes place in one airport (Mitici et al. 2022), while some address scheduling at the network level, including the optimal placement of swapping facilities and the routing of aircraft between airports while monitoring energy states (Kinene and Birolini 2024; Tang et al. 2026)

The charging scheduling for battery swapping in electric aircraft literature employs a variety of optimization approaches, predominantly Mixed-Integer Linear Programming (MILP) and heuristic-based methods. These studies generally aim to balance capital expenditures (CAPEX) for infrastructure with operational expenditures (OPEX), including electricity costs and flight delays. The Table 1 summarizes the optimization techniques and objectives reported in the literature. Several studies employ simulation and metaheuristic approaches to handle the computational complexity, non-convexity, and large-scale characteristics of airport infrastructure and energy systems, which make exact optimization methods difficult to solve directly. Oosterom & Mitici (2023) used Simulated Annealing (SA) to find an approximate solution of infrastructural sizing efficiently. Guo et al. (2023) formulates airport microgrid planning as a heuristic optimization problem to identify Pareto fronts that capture the trade-off between system costs and microgrid resilience. In another study by Kinene et al. (2023), the Kernel Search (KS) heuristic was developed to address large-scale instances of the charging network design problem, which is NP-hard. The approach attains near optimal solutions with significantly lower computational time compared to exact branch-and-cut methods. Simulation-driven techniques are also employed to reduce the complexity of the exact solution. Hellgren & Alfredsson (2026) use a simulation framework that replicates full-day airport operations to assess different infrastructure designs under dynamic conditions and solve a Quadratic Programming (QP) problem.

Table 1. Optimization Techniques and Goals in Battery Swapping Literature

Ref.	Primary Optimization Goal(s)	Optimization Techniques / Algorithms
(Justin et al. 2020)	Power Optimization: Minimize peak-power draw and electricity costs. Power–Investment Optimization: Minimize combined capital costs (batteries/chargers) and recurring energy expenditures.	Scheduling theory, network flow representation, Linear Programming, Ford–Fulkerson method (augmenting paths), and bisection algorithm for charger power throttling.
(Oosterom & Mitici, 2023)	Infrastructure Sizing & Tactical Scheduling: Minimize total costs (charging power, spare batteries, electricity, and flight delays) while accounting for yearly traffic variability.	Two-phase recourse model. Master problem: MILP solved via Simulated Annealing (SA). Subroutine (tactical planning): MILP.
(Mitici et al. 2022)	Logistics & Fleet Sizing: Phase 1—determine fleet size and mission assignments. Phase 2—optimize charging start times, station selection, and minimize spare batteries.	Two-phase MILP with time discretization applied in the second phase to maintain computational tractability.
(Tang et al. 2026)	Minimize the total cost of emissions, charging, swapping, and flight delays for a mixed fleet.	MILP formulation solved using a general-purpose solver (e.g., IBM ILOG CPLEX).
(Guo et al. 2023)	Bi-objective Microgrid Planning: Minimize annualized total cost and maximize microgrid resilience (reduce grid dependency).	Heuristic optimization using NSGA-II (Non-dominated Sorting Genetic Algorithm II) to obtain Pareto fronts.
(Kinene and Birolini 2024)	Strategic Network Design: Trade off the number of charging bases (investment cost) with regional connectivity and population coverage.	Large-scale MILP, multi-commodity network flow formulation, and Kernel Search (KS) heuristic for scalability.
(Bigoni et al. 2018). / (Trainelli et al. 2021)	Infrastructure Sizing: Minimize procurement, maintenance, and energy costs while determining required batteries and chargers.	MILP formulation using Boolean, integer, and continuous variables.

(Doctor et al. 2022)	Congestion Management: Determine optimal number of single- and dual-purpose stands to minimize airside congestion.	Discrete Event Simulation (DES) combined with metaheuristic optimization (Tabu search and scatter search).
(Vehlhaber and Salazar 2024a)	Grid Independence: Minimize reliance on the public grid by dynamically reassigning flights and rescheduling charging using renewable forecasts.	Model Predictive Control (MPC) is formulated as an MILP and solved in a receding horizon framework.

The studies reviewed in the related sources identify several important research gaps, technical limitations, and future directions concerning battery swapping systems for electric aircraft. A notable limitation, noted by Tang et al. (2026), is the assumption of a linear charging profile, which does not accurately capture real battery charging behavior, as charging rates generally taper off as the state of charge increases, especially near full state of charge. Another limitation is that many studies, including (Justin et al. 2020; Vehlhaber and Salazar 2024b) treat flight schedules, energy consumption, and energy availability as deterministic inputs, even though aviation operations are inherently uncertain and subject to considerable variability. To overcome these limitations, this study models the battery's state of charge near full capacity differently to account for its nonlinear behavior. In addition, different schedules for high and low seasons are considered instead of a fixed one. Besides that, the uncertainty in flight schedule is modeled as a noise function added to the arrival and departure time, and to the inbound battery state of charge.

3. Methods

The sizing of airport infrastructure, including the optimal quantities of spare batteries and charging units needed to support battery-swapping operations, is modeled for two traffic models—covering both high and low seasons. The system design is determined by two integer decision variables: n spare, representing the number of fully charged spare batteries available at the start of each day, and C, the number of chargers operating in parallel.

Both variables are subject to predefined upper bounds that reflect practical constraints on infrastructure.
The study develops a stochastic, simulation-based optimization framework for the design and evaluation of airport battery charging and swapping infrastructure under variable traffic conditions. Flight schedules from two scenarios (low-traffic and high-traffic) serve as baseline inputs, and uncertainty in arrival times, departure times, and state of charge is incorporated via Monte Carlo simulation with correlated sampling. For each realization, a non-preemptive scheduling model assigns charging tasks to a limited number of parallel chargers subject to power capacity constraints, discrete charging rates, and operational buffers. Charging durations are estimated using a linear-tapered approximation to reflect reduced charging efficiency at higher states of charge. The charging duration is modeled as a function of the required energy, the state of charge at arrival, and the assigned charging rate. Two charging-time models are supported: a purely linear model and a linear model with tapering penalty. The implemented case uses the linear tapered option. For a job charged at a rate $p \in P$, the base charging time is $T_j^{\text{base}}(p) = \frac{60E_j}{p}$.

Additional operational disruptions, such as stochastic charger failures, are also considered. For each infrastructure configuration—defined by the number of chargers, spare batteries, and available power—the model evaluates key performance indicators including maximum lateness, total lateness, and flight reliability. A day is considered successful if predefined service-level thresholds are met. The overall system reliability is computed as the proportion of successful days across Monte Carlo runs. Finally, a robust design is identified by ensuring feasibility across both traffic scenarios and by constructing a Pareto front based on worst-case performance metrics, enabling the selection of infrastructure configurations that balance cost, capacity, and operational reliability.

The methodology consists of five main stages:
1. Preprocessing the daily schedule and constructing deterministic charging jobs;
2. Generating stochastic daily realizations through Monte Carlo sampling;
3. Simulating non-preemptive charging operations for each infrastructure design;
4. Evaluating reliability and lateness metrics over all Monte Carlo runs;
5. Identifying feasible and Pareto-efficient infrastructure solutions and selecting a final preferred design.

3.1 Optimization Model

The infrastructure design problem can be formulated as a two-stage stochastic mixed-integer linear program, where first-stage decisions determine the number of chargers, spare batteries, and available power capacity, and second-stage decisions correspond to non-preemptive charging scheduling under uncertain operational conditions. However, the presence of discrete scheduling decisions, time-coupled constraints, and probabilistic reliability requirements renders the resulting stochastic program computationally intractable for realistic problem sizes. Therefore, a simulation-based optimization framework is adopted, in which candidate designs are evaluated via Monte Carlo simulation and a non-preemptive scheduling procedure, and robust solutions are identified using Pareto analysis.

The problem can be interpreted as a two-level decision framework. The upper level determines infrastructure design variables (number of chargers, spare batteries, and power capacity), while the lower level evaluates operational performance under uncertainty through simulation-based scheduling. Unlike classical two-stage stochastic programming, the second stage is not solved as an optimization problem but is approximated using a non-preemptive scheduling heuristic embedded within a Monte Carlo simulation framework.

Decision variables

- N^{sp}: Number of spare batteries available at the beginning of the day
- C : Number of chargers installed at the airport
- P^{cap}: Total available airport charging power capacity (kW)
- $t_i^{st} \in R \geq 0$: Start time of charging for job i (min)
- $t_i^{fn} \in R \geq 0$: Completion time of charging for job i (min)
- $t_f^{dep} \in R \geq 0$: Actual departure time of flight f (min)
- $L_i \in R \geq 0$: Lateness of departure i (min)
- $K_i \in K$: Charger assigned to job i
- $x_{ik} \in \{0,1\}$ 1 if job i is assigned to charger k and 0 otherwise
- $y_{ip} \in \{0,1\}$ 1 if job i uses power rate P and 0 otherwise
- $u_{ij}^{k} \in \{0,1\} : 1\ if\ job\ i\ is\ processed\ before\ job\ j\ on\ charger\ k$
- P_i : Charging power assigned to job i (kW)

Objective function

$$\text{Stage 1 (Design): } min\left(N^{sp}, C, P^{cap}, L_{95}^{worst}, \overline{L}^{worst}\right)$$
$$s.t. R^s(b,c,p) \geq \overline{R}, \forall s \in L, H$$

where L_{95}^{worst} and $\overline{L}^{worst}$ are the worst-case 95[th]-percentile maximum lateness and worst-case mean total lateness across both scenarios. This five-dimensional vector is the criterion used to construct the robust Pareto front and select the final design.
The feasible set F consists of all designs satisfying the reliability constraints in both scenarios:

$$F = \left\{(N^{sp}, C, P^{cap}) \middle| R^L \geq \overline{R} \text{ and } R^H \geq \overline{R}\right\}$$

Given a fixed infrastructure design (N^{sp}, C, P^{cap}), the operational problem determines a feasible non-preemptive charging schedule for each scenario realization.

$$\text{Stage 2 (Performance): } min(L_{max}^{95}, L^{tot})$$
s.t.

Charger assignment. Each job is assigned to exactly one charger: $\sum_{k \in K} x_{ik} = 1, \ \forall i \in I.$

Power rate assignment. Each job uses exactly one charging rate: $\sum_{p \in P} y_{ip} = 1, \ \forall i \in I.$
(refer to supplementary section 5.4.1)

The second-stage operational problem determines a feasible non-preemptive charging schedule subject to constraints on charger availability and airport power capacity. The model enforces release times, non-overlapping charger usage, discrete charging-rate selection, and a global power constraint. Due times are treated as soft constraints, and violations are captured through lateness metrics. Battery availability is explicitly modeled through an inventory balance: charged batteries become available upon completion and are assigned to departures in chronological order. Performance metrics, including maximum lateness, total lateness, and reliability, are evaluated after schedule construction and used to assess design feasibility. The proposed model enforces operational feasibility through charger capacity, non-preemptive scheduling, discrete charging-rate selection, and a global airport power constraint. Charging tasks cannot start before their release times and must satisfy minimum turnaround requirements. Battery availability is explicitly modeled, ensuring that each departure is matched with a charged battery.

Performance constraints, including maximum lateness, total lateness, and flight reliability, are evaluated after schedule construction. These metrics are used to determine day success and compute scenario-level reliability. In the design stage, only configurations satisfying the required reliability threshold across all scenarios are considered feasible.

As shown in Algorithm 1, for each candidate design, defined by the number of spare batteries, chargers, and available airport power, the system performance is evaluated under both low- and high-traffic scenarios. Within each scenario, multiple stochastic realizations are generated by perturbing arrival times, departure times, and initial state-of-charge values. For each realization, a non-preemptive charging schedule is constructed subject to charger availability, discrete charging rates, and global power constraints. Charging completion times are then used to determine battery availability and assign batteries to departures, from which lateness and flight reliability are computed. Scenario-level performance metrics, including day reliability, the 95th percentile of maximum lateness, and average total lateness, are obtained by aggregating results across Monte Carlo runs. A design is considered robust-feasible if it satisfies the required reliability threshold in both traffic scenarios. Finally, a Pareto front is constructed over feasible designs, and the optimal design is selected based on prioritized infrastructure and performance criteria.

Algorithm 1 – Charging Infrastructure Design Algorithm

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Algorithm 1 Robust Monte Carlo Algorithm for Airport Charging Infrastructure Design
Data: Low-traffic schedule S^L, High-traffic schedule S^H, design sets B, C, P, Monte Carlo runs N_MC, thresholds
(R̄, L^acc_max, L^acc_tot)
Result: Robust optimal design (b*, c*, p*)
for (b, c, p) ∈ B × C × P do
    for s ∈ {L, H} do
        for r = 1 to N_MC do
            Sample stochastic arrival times, departure times, and arrival SoC
            Construct charging jobs with release times, due times, and energy demands
            Schedule charging tasks (non-preemptive): assign each job to a charger with start time and rate subject to
            charger limit c, power capacity p, and rate levels
            Compute charging completion times and battery availability
            Match charged batteries to departures
            Compute lateness L^(r,s)_max, L^(r,s)_tot and flight reliability R^(r,s)
        Compute scenario metrics: R^s = (1/N_MC) ∑ 1_success   P95^s = 95th percentile of L^(r,s)_max   L̄^s = mean of L^(r,s)_tot
    Compute robust metrics: R^worst = min(R^L, R^H)   P95^worst = max(P95^L, P95^H)   L̄^worst = max(L̄^L, L̄^H)
Select feasible designs satisfying: R^L ≥ R̄ and R^H ≥ R̄
Construct Pareto front in (b, c, p, P95^worst, L̄^worst)
Select final design (b*, c*, p*) from Pareto set
```

In which parameters are defined in Table 2.

Table 2. Algorithm's Parameters

Parameter	Description
Input Data	
S^L	Flight schedule under low-traffic scenario
S^H	Flight schedule under high-traffic scenario
B	Set of candidate values for spare batteries ($b \in B$)
C	Set of candidate values for number of chargers ($c \in C$)
P	Set of candidate values for airport power capacity ($p \in P$)
N_{MC}	Number of Monte Carlo simulation runs
$\bar{R}$	Required day reliability threshold
L^{acc}_{max}	Acceptable maximum lateness threshold [min]
L^{acc}_{tot}	Acceptable total lateness threshold [min]
Indices	
$b \in B$	Candidate number of spare batteries
$c \in C$	Candidate number of chargers
$p \in P$	Candidate airport power capacity
$s \in \{L, H\}$	Traffic scenario index (low or high)
$r = 1, \ldots, N_{MC}$	Monte Carlo realization index
Monte Carlo Outputs (per realization)	
$L^{(r,s)}_{max}$	Maximum lateness in realization r under scenario s [min]
$L^{(r,s)}_{tot}$	Total lateness in realization r under scenario s [min]
$R^{(r,s)}$	Flight reliability in realization r under scenario s
Scenario-Level Metrics	
R^s	Day reliability for scenario s, $R^s = \frac{1}{N_{MC}} \sum_{r=1}^{N_{MC}} \mathbf{1}_{\text{success}}$
$P95^s$	95th percentile of $L^{(r,s)}_{max}$ over all Monte Carlo runs
$\bar{L}^s$	Mean of $L^{(r,s)}_{tot}$ over all Monte Carlo runs
Robust Aggregated Metrics	
R^{worst}	Worst-case reliability across scenarios, $R^{worst} = \min(R^L, R^H)$
$P95^{worst}$	Worst-case 95th percentile lateness, $P95^{worst} = \max(P95^L, P95^H)$
$\bar{L}^{worst}$	Worst-case mean total lateness, $\bar{L}^{worst} = \max(\bar{L}^L, \bar{L}^H)$
Design Variables (as used in Algorithm)	
(b, c, p)	Candidate design (spare batteries, chargers, power capacity)
(b^*, c^*, p^*)	Selected optimal design from the Pareto set

3.2 Arrival, Departure, and Charging Jobs

The model uses flight-schedule data from airport operations. Each dataset consists of three key variables for each flight: arrival time, departure time, and state-of-charge (SOC) upon arrival, which is a uniformly distributed random variable in the interval of [0.2, 0.35]. These variables define charging jobs, including release times, due times, and energy requirements. In addition, a Monte Carlo–driven simulation framework that captures the stochastic interactions among aircraft arrivals, departures, and battery charging processes. Days are treated as independent realizations of airport operations and form the empirical basis for Monte Carlo sampling.

Two datasets are considered to represent different traffic conditions: a low-traffic scenario and a high-traffic scenario. Each scenario is modeled as a set of flights:

$$S^s = \{(t_i^{arr},\ t_i^{dep},\ SOC_i^{arr})\}_{i \in \mathcal{I}}, \quad s \in \{L, H\}.$$

From these inputs, the model derives the release time and due time of each charging job as:

$$r_i = t_i^{arr} + \tau^{tr},$$
$$d_i = t_i^{dep} - \tau^{tr},$$

and the required charging energy as:

$$E_i = \max(0, (SOC^{tar} - SOC_i^{arr}) E^{batt}).$$

To account for operational uncertainty, stochastic variations are introduced to arrival times, departure times, and initial SOC values using correlated normal distributions. These perturbations enable the evaluation of system performance under realistic variability conditions.

3.3 Power Allocation Mechanism

Charging jobs are scheduled using a non-preemptive, event-driven procedure. At each decision epoch, jobs that have been released but not yet scheduled are considered. The available charging power is given by:

$$P^{avail}(t) = p - \sum_{i \in \mathcal{A}(t)} p_i,$$

where $\mathcal{A}(t)$ is the set of active charging jobs. Among all waiting jobs, the job with the minimum slack is selected, where slack is defined as: $Slack_i = d_i - (t + \delta_i)$, with δ_i denoting the charging duration. The charging rate is selected from a discrete set of feasible rates such that the total power does not exceed the available capacity. The algorithm first attempts to assign the highest feasible charging rate and then reduces it if a lower rate is sufficient to complete charging before the due time.

Each job is assigned to the first available charger and processed without interruption until completion. If no feasible assignment is possible, the simulation time advances to the next event, either a job release or a charging completion.

3.4 Reliability and Lateness

Operational reliability is evaluated using a Monte Carlo framework. For each simulated day, a flight is considered successful if its departure delay does not exceed a predefined threshold. The flight reliability is defined as the proportion of successful departures. A day is classified as successful if three conditions are simultaneously satisfied: (i) the maximum lateness does not exceed a specified bound, (ii) the total lateness remains below a threshold proportional to the number of flights, and (iii) the flight reliability exceeds a required level. The overall day reliability is then defined as the proportion of successful days across all Monte Carlo simulations. In the robust design setting, a solution is considered feasible only if the required day reliability is satisfied under both low- and high-traffic scenarios. Lateness is defined as the positive deviation between the actual and scheduled departure times. For each flight, lateness is computed as the difference between the actual departure time, which depends on battery availability, and the scheduled departure time. Three lateness metrics are considered: (i) flight-level lateness, (ii) maximum lateness across all flights within a day, and (iii) total lateness accumulated over all flights. These metrics capture individual service quality, worst-case delay, and overall system congestion, respectively. In the proposed framework, lateness is not directly minimized but is incorporated into reliability constraints. Specifically, a simulated day is considered successful if both the maximum lateness and total lateness remain below predefined thresholds. Additionally, lateness distributions across Monte Carlo simulations are used to compute statistical performance indicators, including the mean total lateness and the 95th percentile of maximum lateness. For a detailed reliability mathematical model, refer to section 5.6 of the supplementary material.

3.5 Cost Function

The infrastructure cost is modeled as a linear function of the number of spare batteries, chargers, and installed airport power capacity. The coefficients are normalized cost weights used to compare alternative designs. The cost function is a linear infrastructure cost and is defined as:

$$Z = Cost(b, c, p) = c^{sp}b + c^{ch}c + c^{pw}p$$

where:

- b: number of spare batteries
- c: number of chargers
- p: airport power capacity
- Z: total infrastructure cost
- c^{sp}: unit cost of one spare battery
- c^{ch}: unit cost of one charger
- c^{pw}: unit cost per kW of installed airport power

In the model, the cost is mainly used for reporting and trade-off visualization, while the final selection is still sorted lexicographically by batteries, chargers, power, and lateness, not by minimum total cost alone.

3.6 Selection of Pareto Set

A Pareto dominance approach is employed to identify non-dominated infrastructure designs. Each candidate solution is evaluated using five criteria: number of spare batteries, number of chargers, airport power capacity, worst-case 95th percentile of maximum lateness, and worst-case mean total lateness. A design is considered Pareto-dominated if another design performs no worse in all criteria and strictly better in at least one. The Pareto set is the set of solutions that are not dominated by any other solution in the feasible set. From the Pareto-optimal set, a final design is selected using a lexicographic ordering that prioritizes minimizing the number of spare batteries, followed by the number of chargers, airport power capacity, and lateness metrics.

4. Results and Discussion

4.1 Numerical Assumptions

The battery capacity is set to 214 kWh, and the target SOC is fixed at 90%. Charging is performed using discrete charger power levels ranging from 60 to 150 kW with a 15 kW step, and a linear-tapered charging model is applied beyond 80% SOC, with a penalty factor of 1.15 to improve accuracy and model charging nonlinear behavior. A handling time of 5 minutes for removing a depleted battery is considered. Uncertainty is modeled through Monte Carlo simulation with 500 realizations, incorporating stochastic variations in arrival times, departure times, and initial SOC values. Arrival/ departure time distribution over one low traffic and high traffic day is illustrated in Figure 1 and Figure 2 respectively. The number of departures reaches 3 in low traffic and 13 in high traffic per 30 minutes at peak time in the input data. The standard deviations are set to 5 minutes for arrival and departure times, and 0.05 for SOC, with correlated sampling applied. Operational disruptions are modeled with a 2% failure probability, resulting in an additional 10-minute delay. The design space includes 0 to 10 spare batteries, 1 to 20 chargers, and airport power capacities ranging from 500 kW to 2000 kW with 150 kW steps.

Figure 1. Low Traffic Arrival/ Departure Distribution

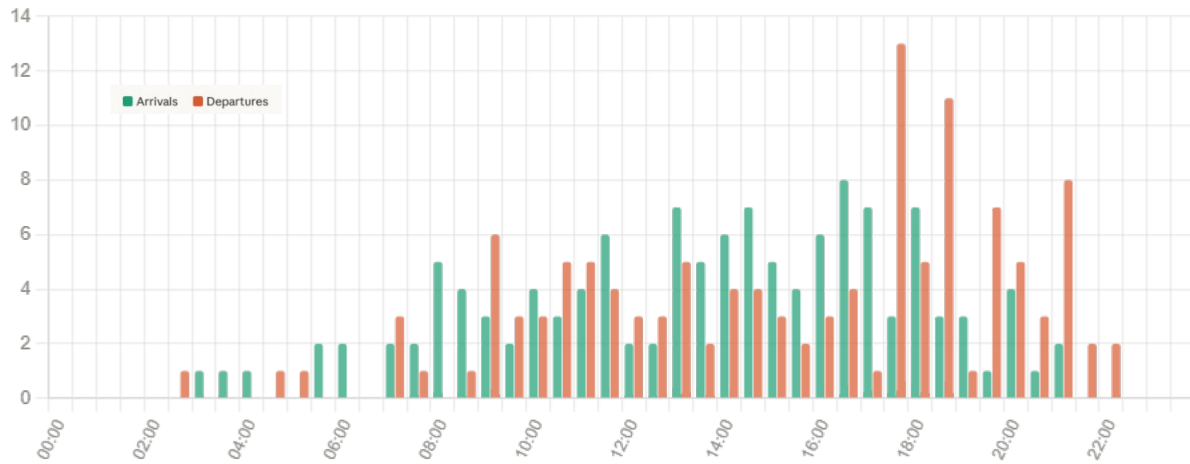

Figure 2. High Traffic Arrival/ Departure Distribution

Performance thresholds are defined as 15 minutes for acceptable flight delay and maximum lateness, and 100 minutes for total lateness in a one-day operation. The required reliability levels are set to 95% for both flight-level and day-level performance. Cost parameters are normalized, with unit costs assigned to spare batteries and chargers, and a proportional cost applied to installed power capacity.

In the model, the cost is mainly used for reporting and trade-off visualization, not for feasibility assessment. The coefficients are normalized cost weights used to compare alternative designs. The cost of designing and installing charging facilities varies based on factors such as electricity generation method and battery capacity. Grid connection costs for 70 € per kW, and each 60kW charger may cost about 40,000 € (Bigoni et al. 2018). However, according to Guo et al. (2020), smaller chargers for swapping stations are listed at £10,000 per unit. Battery price, on the other hand, according to Justin et al. (2020), is around 100$/kWh. So, in our case, it is around 21,400$. Therefore, in the model, the battery weight and charger investment costs are set to 1 each, while the airport power capacity development is set to 0.05 per kW.

4.2 Numerical Results

The solution provides a fixed high- and low-traffic charging schedule while optimizing the number of chargers, spare batteries, and required maximum power. The problem is solved using MATLAB

According to the priorities defined by the problem, the best design combination of (B=1, C=10, P=1550kW), which meets the requirements of both high and low traffic, is shown in Table 3 and Table 4. As expected, the values of P95

Max Lateness, Mean Total Lateness, Mean Flight Reliability, and Day Reliability not only meet the feasibility assumptions of the problem, but also represent the logic of the code for the priority of minimum battery, charger, and power, and minimum Worst P95 Max Lateness and Worst Mean Total Lateness which are 10.355 and 8.786 minutes, respectively.

Table 3. Low traffic best design from the Pareto front results

Low traffic Scenario						
Mean Max Lateness	P95 Max Lateness	Mean Total Lateness	Mean Flight Reliability	Day Reliability	Successful Days	N_MC_used
0.103	0.000	0.103	1	1	500	500

Table 4 - High traffic best design from the Pareto front results

High traffic Scenario						
Mean Max Lateness	P95 Max Lateness	Mean Total Lateness	Mean Flight Reliability	Day Reliability	Successful Days	N_MC_used
4.135	9.064	7.914	0.99997	0.996	498	500

4.3 Graphical Results

Figure 3 shows the charging rate distribution for the optimal design (B = 1, C = 10, P = 1550 kW) under both traffic scenarios. The bimodal pattern — concentrated at 100 kW and 180 kW — reflects the power-aware scheduling logic, which alternates between full-speed charging and throttled operation to respect the grid limit. The shape is consistent across both traffic levels, indicating that the heuristic scales reliably with demand.

Figure 4 presents the lateness exceedance curves under high- and low-traffic conditions. Under high traffic, both the maximum and total lateness curves fall below the 15-minute threshold, confirming design feasibility even on adverse days. Under low traffic, both curves collapse within the first few minutes, consistent with the near-perfect day reliability reported in Table 3. Together, these figures confirm that the selected infrastructure design maintains robust service performance across the full seasonal range. Figure 5 presents the robust Pareto front in three dimensions — spare batteries, chargers, and worst-case P95 maximum lateness — colored by airport power capacity. The clustering of low-lateness solutions around 1400–1550 kW confirms that power capacity is a binding constraint, and that the three design variables must be evaluated jointly rather than independently.

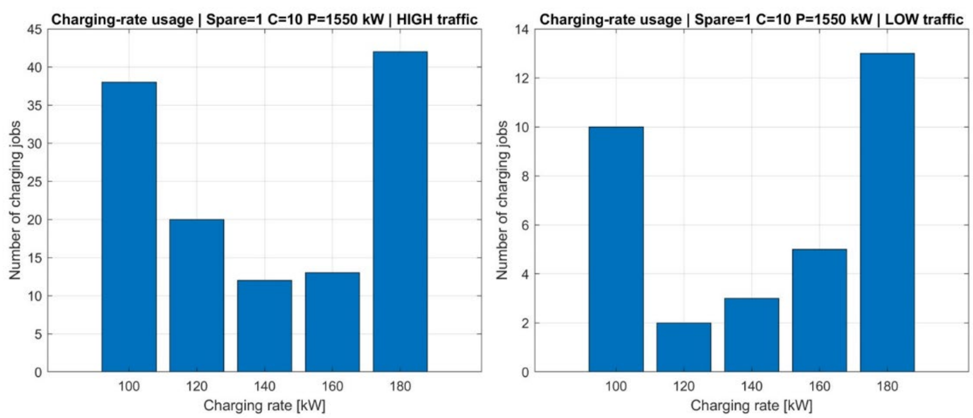

Figure 2. Charging-rate usage distribution for the optimal design (B = 1, C = 10, P = 1550 kW) under high-traffic (left) and low-traffic (right) conditions.

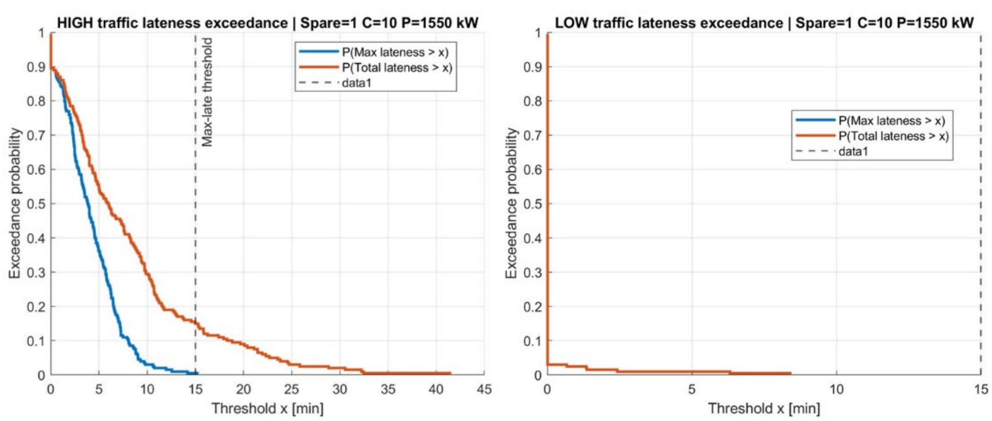

Figure 3. Lateness exceedance probability curves for the optimal design under high-traffic (left) and low-traffic (right) conditions. The dashed vertical line marks the 15-minute maximum lateness threshold.

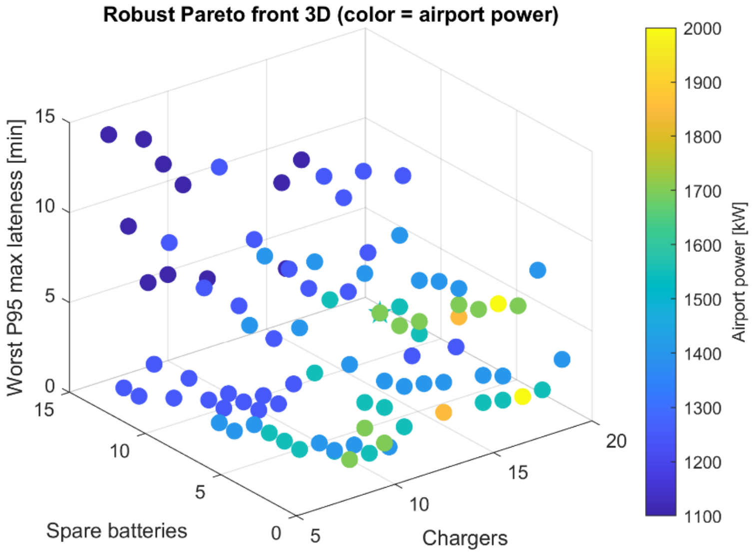

Figure 4. Robust Pareto front in three dimensions (spare batteries × chargers × worst-case P95 maximum lateness), colored by airport power capacity (kW)

4.4 Other possible best Designs

When we consider cost as well, along with the minimum battery, charger, and power requirements, the balanced Pareto solution is B=3, C=11, and P=1400kW. In Figure 6, all feasible solutions and their normalized cost values are illustrated as colored dots, with the total cost indicated. However, all the Pareto fronts can be considered by designers according to their priorities, as shown in Table 5.

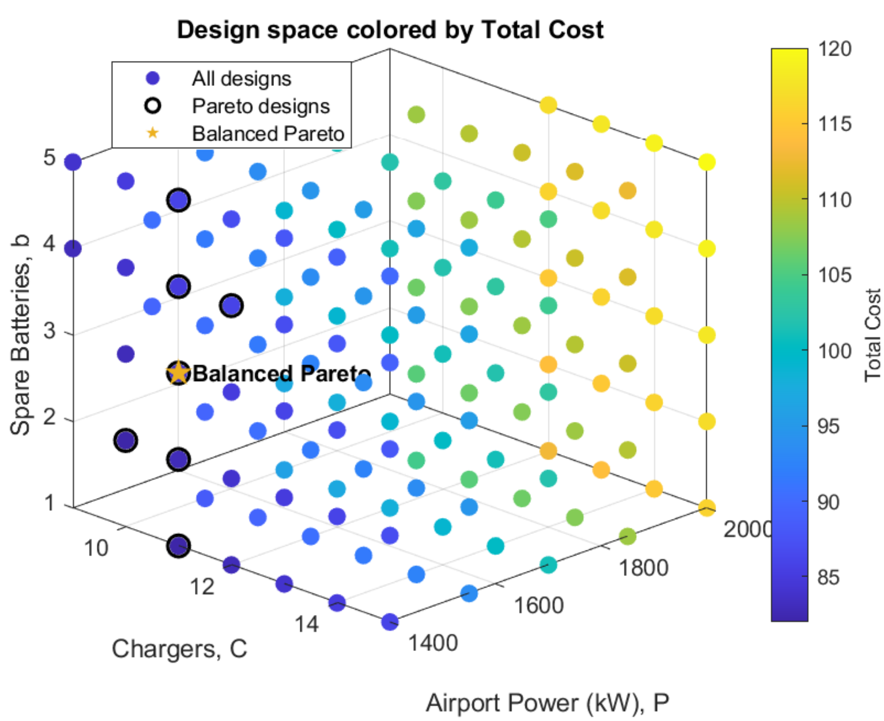

Figure 5. Feasible solutions, Pareto front, and Balanced Pareto affected by the normalized total cost value

Table 5. Offered Pareto fronts (considering normalized cost value)

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B	C	P_kW	Worst P95 Max Lateness	Worst Mean Total Lateness	Worst Mean Flight Reliability	Worst Day Reliability	Total Cost
3	**11**	**1400**	**0**	**0.088**	**1**	**1**	**84**
1	11	1400	10.86	8.43	0.999888	0.986	82
2	10	1400	11.16	6.87	0.999776	0.98	82
2	11	1400	4.10	0.78	1	1	83
4	11	1400	0.00	0.00	1	1	85
5	11	1400	0	0	1	1	86
4	12	1400	0	0	1	1	86

4.5 Sensitivity Analysis

A sensitivity analysis was conducted to examine how the optimal infrastructure configuration and associated performance metrics respond to variations in key model parameters. The analysis considers changes in the numbers of chargers and spare batteries, as well as available airport power capacity, across the feasible design space. Figure 4 presents reliability heatmaps and lateness contour plots as functions of these design variables for both the low-traffic and high-traffic scenarios. The results confirm that day reliability is most sensitive to the number of chargers in the high-traffic scenario, where insufficient charger capacity rapidly degrades both flight reliability and maximum lateness. In contrast, spare battery count plays a more critical role under moderate-to-high traffic when departure bursts occur, as a depleted battery inventory can trigger cascading delays even when charger capacity is adequate. Power capacity becomes a binding constraint primarily at higher charger counts, where simultaneous fast charging may exceed grid limits. Together, these sensitivities demonstrate that the three design variables interact non-trivially and that evaluating them jointly—as done in the proposed framework—is essential for identifying robust and cost-efficient solutions (Figure 7).

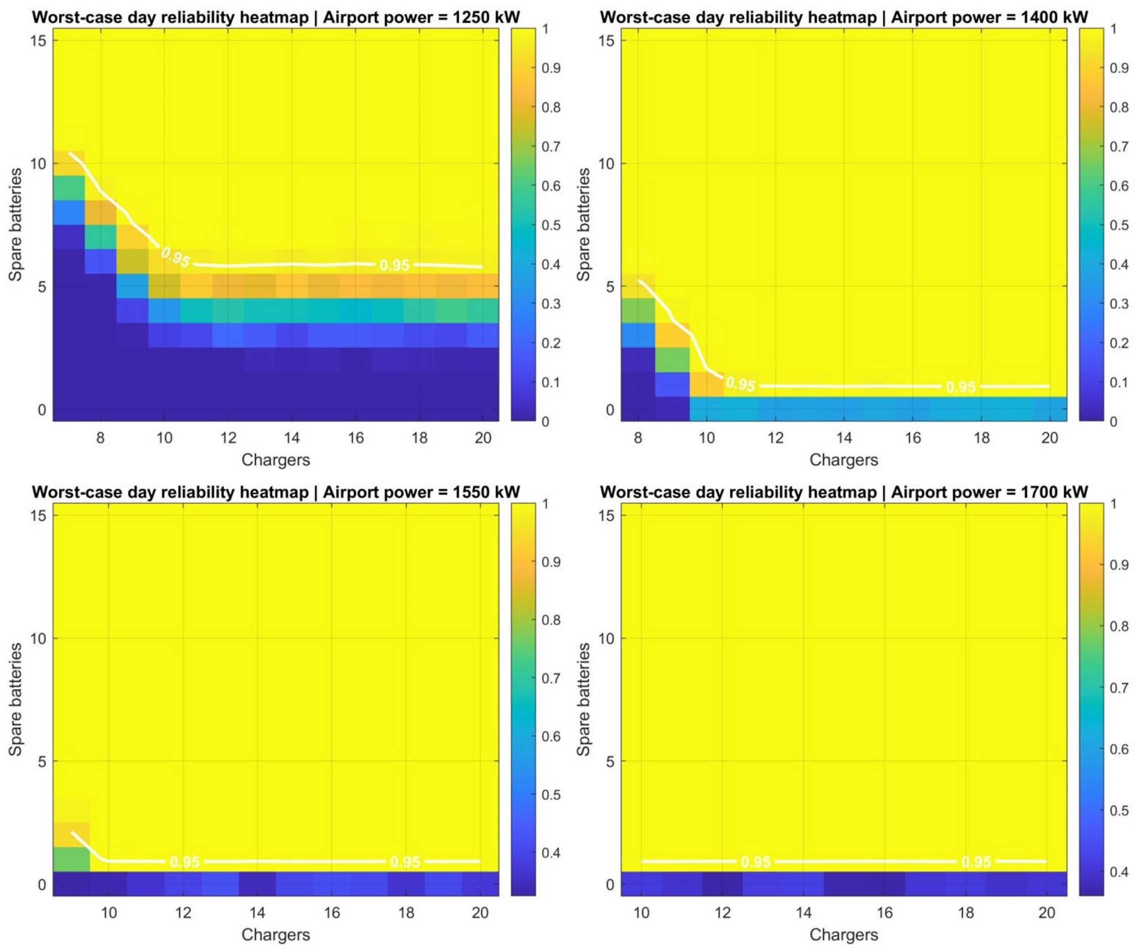

Figure 6. Sensitivity of ground infrastructure reliability to airport power capacity: worst-case day simulation results for charger and spare battery configurations

4.6 Medium Traffic Validity Analysis

To validate the robustness of the simulation-based design, an exact Mixed-Integer Linear Program (MILP) was solved for a medium-traffic operating day using the optimal infrastructure configuration identified in the previous section (B=1, C=10, P=1550 kW). The exact MILP enforces the same non-preemptive scheduling constraints, discrete charging rates, power capacity limits, and battery availability rules as the heuristic, but guarantees a globally optimal schedule for the given instance. The results confirm full operational feasibility: all departures were served without battery shortfalls, the total accumulated lateness was 25.00 minutes, the maximum single-flight lateness was 10.00 minutes, and flight reliability reached 1.0. Peak power consumption reached 1,300 kW, remaining within the 1,550 kW grid capacity, and eight of the ten available chargers were active during peak demand. These outcomes are consistent with the Monte Carlo simulation predictions for the high-traffic scenario, confirming that the heuristic-based framework provides reliable performance estimates and that the selected infrastructure design generalizes effectively to intermediate traffic levels not explicitly included in the training scenarios. Figure 8 illustrates the optimal charging schedule produced by the exact MILP solution.

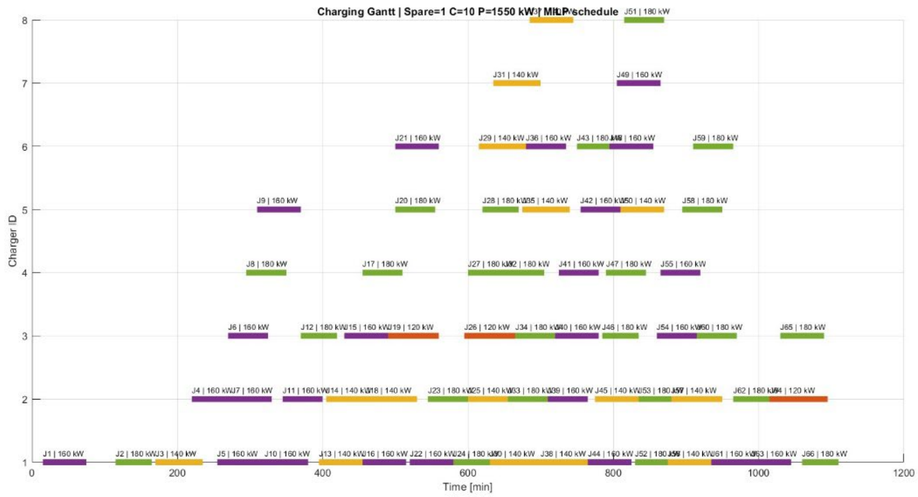

Figure 7. Optimal Charging Schedule

5. Conclusion

This study presented a stochastic simulation-based optimization framework for sizing airport battery-swapping and charging infrastructure to support electric aircraft operations under realistic operational uncertainty. The framework addressed three research gaps identified in the literature: (i) the assumption of deterministic flight schedules and energy inputs used by Justin et al. (2020) and Vehlhaber and Salazar (2024b), which this work overcomes through Monte Carlo simulation with correlated perturbations to arrival times, departure times, and state-of-charge values; (ii) the reliance on a single representative day for infrastructure sizing, as critiqued by Oosterom and Mitici (2023), which is resolved here by evaluating designs against both low- and high-traffic seasonal scenarios simultaneously; and (iii) the linear charging profile assumption of Tang et al. (2026), which is improved by incorporating a linear-tapered model with a penalty factor beyond 80% state of charge to better reflect real battery behavior near full capacity.

All stated objectives were met. The framework successfully determined the optimal infrastructure configuration—one spare battery, ten chargers, and 1,550 kW of installed power capacity—that satisfies the required 95% reliability threshold under both low- and high-traffic conditions. For the low-traffic scenario, the design achieved perfect performance with a mean maximum lateness of 0.103 minutes and a day reliability of 100%. For the high-traffic scenario, the design maintained a mean flight reliability of 99.997% and a day reliability of 99.6%, with the worst-case 95th-percentile maximum lateness of 10.355 minutes and worst-case mean total lateness of 8.786 minutes remaining within the acceptable bounds of 15 minutes and 100 minutes, respectively. When cost is incorporated as an additional criterion alongside the Pareto analysis, the balanced design shifts to three spare batteries, eleven chargers, and 1,400 kW, which achieves perfect reliability across both seasons and a normalized total infrastructure cost of 84 units, representing a modest increase in battery inventory that yields a significant reduction in worst-case lateness.

The validity of the simulation-based approach was further confirmed by an exact MILP benchmark on a medium-traffic schedule using the optimal design parameters. The exact solver produced a total lateness of 25.00 minutes, a maximum lateness of 10.00 minutes, perfect flight reliability, and a peak power draw of 1,300 kW utilizing eight active chargers—all within the feasibility thresholds and consistent with the simulation framework's predictions. This cross-validation demonstrates that the greedy simulation-based heuristic provides reliable performance estimates without the computational burden of exact MILP approaches, making it suitable for evaluating large design spaces.

The unique contributions of this research are threefold. First, the study introduces a robust, multi-scenario infrastructure sizing methodology that simultaneously guarantees service reliability under both peak and off-peak seasonal traffic—a capability absent in single-day or average-day optimization approaches such as those by Justin et al. (2020) and Mitici et al. (2022). Second, by coupling grid capacity explicitly as a first-stage design variable alongside battery inventory and charger count, the framework enables decision-makers to quantify the cost implications of grid reinforcement and to identify configurations where upgrading power capacity can substitute for additional physical assets.

Third, the integration of operational disruptions, including stochastic charger failures and correlated schedule variability, into the Monte Carlo simulation provides a more realistic characterization of system reliability than deterministic scheduling models. Together, these features offer airport planners and policymakers a transparent, computationally tractable tool for evaluating the trade-space between infrastructure investment and operational performance as aviation electrification advances.

Future research should integrate airport charging and battery-swapping infrastructure with renewable energy sources, battery energy storage systems, and smart-grid operations. In addition, advanced scheduling approaches such as machine learning and reinforcement learning can be explored to improve operational efficiency under uncertain flight schedules, battery degradation, and electricity price variations. Finally, extending the framework to a multi-airport network would provide a more comprehensive assessment of electric aircraft infrastructure requirements.

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