Impact of Aviation Electrification on Airports: Flight Scheduling and Charging

Boya Hou¹,*, Subhonmesh Bose¹, Lavanya Marla², Kiruba Haran¹

Abstract
Electrification can help to reduce the carbon footprint of aviation. The transition away from jet fuel-powered conventional airplane towards battery-powered electrified aircraft will impose extra charging requirements on airports. In this paper, we first quantify the increase in energy demands at several airports across the United States (US), when commercial airline carriers partially deploy hybrid electric aircraft (HEA). We then illustrate that smart charging and minor modifications to flight schedules can substantially reduce peak power demands, and in turn the needs for grid infrastructure upgrade. Motivated by our data analysis, we then formulate an optimization problem for slot allocation that incorporates HEA charging considerations. This problem jointly decides flight schedules and charging profiles to manage airport congestion and peak power demands. We illustrate the efficacy of our formulation through a case study on the John F. Kennedy International Airport.

Keywords:
Electric aircraft, Slot Allocation, Smart charging

1. Introduction
Commercial aviation produced 915 million tonnes of CO₂ worldwide in 2019, responsible for 2% of all human-induced CO₂ emissions from energy consumption, as per the Air Transport Action Group [1]. The carbon footprint of aviation is projected to increase with predicted annual growth of 4.2% in demand for air travel over 2018-2038, according to the International Civil Aviation Organization [2]. The corresponding increase in greenhouse gas emissions will pose a serious threat to the vision of a carbon-neutral future. Electrification has been identified as a potential path to reduce said emissions, e.g., by the National Academies of Sciences Engineering and Medicine [3].

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Electrified aircraft are an emergent technology, largely enabled by the development efforts supported by NASA’s Advanced Air Transport Technologies program in the United States and similar programs by the respective agencies in the European Union and Asia. Various aircraft configurations such as turbo-electric, hybrid-electric and all-electric have been proposed and analyzed. For example, flight performance of parallel turbofan systems has been analyzed in Gladin et al. [4]. The benefits of a parallel hybrid propulsion system for boosting power during takeoff and climb has been demonstrated in Lents et al. [5] and Bertrand et al. [6]. Small electric airplanes for general aviation are already available. Flight demonstrations are underway for the commuter class with planes carrying <20 passengers. The next step is to electrify regional airplanes that accommodate 30 - 100 passengers. Various studies such as those in Schäfer et al. [7], Wroblewski and Ansell [8] predict commercial aviation to adopt electric aircraft over the next few decades (2030-2050 time-frame).

To handle the impending electrification of commercial aviation, airports must invest in appropriate charging infrastructure. Investment into building such infrastructure must be forward-looking and account for plausible growth trajectories of electrification technology. The first aim of this paper is to provide a framework to gauge the energy and power needs of hybrid electric aircraft (HEA) at major airports across the United States (US). By hybrid electric configuration, we mean those airplanes which are propelled partly by electric motor through a battery system and partly by gas turbines through jet fuel. As will become clear, we only consider those configurations that are deemed to become viable over 2030-2050, according to academic and industrial research. Scheduling of flights at an airport is intimately related to when and how much the electrified ones can be charged. As we demonstrate, one substantially impacts the other. The second and final aim of this paper is the formulation and solution of a slot allocation problem that models charging considerations of HEA at airports. That is, the slot allocation problem jointly schedules flight arrivals/departures and decides the charging profiles of HEA, aiming to minimize airport congestion and peak electric power demands from HEA.

Not all flights can be operated using HEA. Energy densities of today’s batteries are in the 200-250 Wh/kg range. They are substantially smaller than that of jet fuel with densities of ∼13,000 Wh/kg. As a result, the size and the weight of a battery required on board limits the range of an HEA. The battery size also depends on the extent the aircraft relies on electric propulsion as opposed to jet fuel. With plausible configurations of battery energy densities and degree of hybridization, we compute the energy needs for operating HEA on domestic flight paths within continental US in Section 2. By switching flights from current schedules that can be operated by HEA, we estimate the increase in annual energy needs at various US airports. Our estimates indicate that accommodating HEA in commercial aviation will require substantial upgrades to the grid infrastructure that powers these airports.

While flight distance, number of passengers and airplane type largely dictate the energy needs for an HEA, peak power requirements from the grid on the other hand, depend on the rate of charging. Grid components must be sized properly to support such peaks. In Section 3, we show that charging HEA at constant power levels over their dwell times
at airports can lead to substantial peak power demands. Optimizing charging schedules can significantly lower these peaks at airports.

Flight arrival and departure schedules define the dwell times of flights at airports. For HEA, these schedules put constraints on when and how much to charge each airplane. Not surprisingly, alterations in schedules of some flights can further shrink peak power requirements over and above that obtained from optimizing charging schedules alone. Our results in Section 3 indeed align with this expectation. Charging considerations alone cannot define flight schedules, however. Airlines tailor their requests for flight arrivals and departures to suit passenger demand patterns. As a result, busy airports often witness congestion during peak hours, given the runway capacities. Congestion leads to flight delays at these airports. Such delays for multi-hop flight paths tend to cascade across airports. Planning flight schedules via slot allocation for congestion management has been widely recognized, e.g., see Zografos et al. [9] for a survey. We formulate a slot allocation problem that accounts for charging considerations of HEA in Section 4. Specifically, we design an optimization program that seeks to jointly minimize the displacements of flights from their requested schedules and flatten the power profile required to charge the HEA aircraft operating these schedules.

We run a representative case study of slot allocation problem with HEA charging for the John F. Kennedy International Airport (JFK) in Section 5. Our experiments reveal the importance of jointly considering slot allocation and smart HEA charging with reasonable HEA adoption. In particular, we solve a slot allocation problem without HEA charging considerations and then construct charging profiles for HEA under a constant power charging scheme. Such a construction results in a high peak power demand of 35.9 MW. Enforcing a limit of 20 MW on power drawn for charging, our slot allocation problem reduces that peak to 14.6 MW with a different flight schedule. Using our simulation framework, we also study how runway capacities at the airport and charging constraints on airplane batteries impact both flight schedules and charging profiles. The results illustrate that congestion and charging considerations are inter-dependent and cannot be tackled separately.

The key contributions of this paper are as follows. First, we present a framework to study the impact of HEA adoption within commercial aviation. To the best of our knowledge, this is the first paper that jointly tackles transportation and grid considerations with HEA. Second, we demonstrate that charging schedules for HEA must be optimized carefully to prevent large peak power demands. Lacking such a design, peak power requirements will put unnecessary burdens on the supporting grid infrastructure. Our third contribution is the slot allocation model with HEA charging. To our knowledge, this is the first work that provides a framework for managing airport congestion and HEA charging together. The case study on JFK airport indicates how one cannot disentangle these two problems.

1.1. Literature review

We draw on two lines of work— one that characterizes the capabilities and impacts of electric airplanes, and the other that studies slot allocation for flight scheduling. In
the first line of research, the most relevant works are those of Wroblewski and Ansell [8], Gnadt et al. [10] that quantify the capabilities of HEA concepts. We focus on retrofitted regional and single-aisle HEA configurations in Table 1 that academic and industry research deem viable over the next few decades. Leveraging the technology growth scenarios envisioned in these works, we examine the impacts of HEA adoption on airport operations. We remark that aggregate electricity consumption in the US from electric airplanes has been estimated in Schäfer et al. [7]. These estimates are based on the uniform adoption scenario of a 180-passenger all-electric airplane, studied in Gnadt et al. [10]. In contrast, we provide a detailed systematic framework to study airport operations with much more realistic retrofitted HEA.

Table 1: Summary of regional and single-aisle hybrid electric aircraft concepts and research. BSED stands for battery specific energy density.

<table>
<thead>
<tr>
<th>Research group</th>
<th>Hybrid architecture</th>
<th>BSED (Wh/kg)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boeing-GE SUGAR Volt</td>
<td>Parallel</td>
<td>750</td>
<td>Bradley and Droney [11, 12]</td>
</tr>
<tr>
<td>Bauhaus</td>
<td>Parallel</td>
<td>1000-1500</td>
<td>Pornet et al. [13]</td>
</tr>
<tr>
<td>UTRC</td>
<td>Parallel</td>
<td>Not spec.</td>
<td>National Academies of Sciences Engineering and Medicine [3]</td>
</tr>
<tr>
<td>Airbus Series</td>
<td>800</td>
<td>Delhaye and Rostek [14]</td>
<td></td>
</tr>
<tr>
<td>Cambridge Parallel</td>
<td>750</td>
<td>Friedrich and Robertson [15]</td>
<td></td>
</tr>
<tr>
<td>Georgia Tech Parallel</td>
<td>750</td>
<td>National Academies of Sciences Engineering and Medicine [3]</td>
<td></td>
</tr>
</tbody>
</table>

In the second category, there is a growing literature on flight scheduling at capacity-constrained airports. See NERA Economic Consulting [16], Czerny et al. [17], Corollí et al. [18], Benlic [19], Zografos et al. [9], Pyrgiotis and Odoni [20], Jacquillat and Odoni [21], Ribeiro et al. [22, 23] among others. These papers optimize flight schedules to limit congestion during peak hours at airports to avoid flight delays, the total cost of which in the US has been estimated to be $33 billion by the Federal Aviation Administration [24]. We build on these models to co-optimize schedules of all flights and the charging profiles of HEA at capacity-constrained airports.

2. Estimating Energy Requirements of HEA

Energy needs of operating a flight path with HEA will depend on the the type of aircraft being electrified and the distances traveled. For flight paths, we focus on short-haul domestic commercial flights that had a dwell time longer than 15 minutes at the originating airport in 2018. We use flight information from the airline on-time performance data from the US Department of Transportation’s Bureau of Transportation Statistics (BTS)
The range of an HEA is limited by the size and weight of the battery on-board. Battery technology for electric airplanes is constantly improving. These batteries are characterized by two parameters—its battery specific energy density (BSED) and its motor factor (MF). BSED, measured in Wh/kg, dictates the weight of the battery required to deliver a given amount of electrical energy. And, MF defines the ratio of the peak power that can be delivered by the battery and that required by the aircraft. For a specific BSED-MF combination, we utilize the range capabilities of retrofit hybrid electric regional jets and narrow body aircraft from Wroblewski and Ansell [8], reproduced in Appendix Table A.2. A specific flight can utilize HEA only if the flight distance is within this range.

We now formally describe the electrical energy requirement of operating a flight path with HEA. Assume that each HEA arrives at an airport with a depleted battery and needs to be charged up to the level required for its next flight. The required energy is calculated as \( E = p \times d \times b_0 \), where \( d \) describes the next flight distance in miles, \( p \) is the number of passengers and \( b_0 \) denotes the battery energy usage per passenger-mile. This calculation assumes that the electrical power drawn from the battery remains roughly constant during different phases of the flight, e.g. taxi, take-off and landing. For each flight in the database from the US Department of Transportation’s Bureau of Transportation Statistics (BTS) [25], we use the tail-number to identify the aircraft type from airplane manufacturer’s websites; which in turn, yields the total number of seats on the plane. Throughout this analysis, we uniformly assume that 85% of all seats are filled in each flight to estimate \( p \). This load factor matches the yearly average estimates of the same in the industry, based on the US Department of Transportation’s Bureau of Transportation Statistics (BTS) [26]. The values of parameter \( b_0 \) for HEA are adopted from Wroblewski and Ansell [8], reproduced in Table A.1 in the Appendix, assuming a battery-pack voltage of 128V. Sizing of such batteries accounts for battery energy consumed during taxi, takeoff, cruise, approach, and landing. For regional jets, we use \( b_0 \) for ERJ-175 and for single-aisle aircraft, we use that for Boeing 737-700.

To illustrate the calculations through an example, consider a single hybrid electric retrofit of Embraer ERJ 170-200 aircraft with tail number N178SY. On 05/29/2018, this aircraft operated a 599-mile flight from SFO (San Francisco International Airport, CA) to SLC (Salt Lake City, UT). N178SY arrived at SFO at 17:02 pm and left for SLC at 17:53 pm. For different MF and BSED configurations, Table 2 records \( E \). For this example, a BSED of 500 Wh/kg and and MF of 25% does not have the range ability to cover 599 miles. As a result, with this BSED-MF combination, N178SY cannot be operated with HEA.

Table 2: Power requirements of N178SY for flight from SFO to SLC.

<table>
<thead>
<tr>
<th>MF (%)</th>
<th>BSED (Wh/kg)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>500</td>
<td>700</td>
</tr>
<tr>
<td>12.5</td>
<td>1.05 MWh</td>
<td>1.03 MWh</td>
</tr>
<tr>
<td>25</td>
<td>/</td>
<td>2.14 MWh</td>
</tr>
</tbody>
</table>
2.1. Annual Energy Requirements at US Airports

The energy demands for individual flights under BSED-MF combinations prove useful in later sections to both analyze and design charging schedules for HEA. Here, we utilize our calculations to estimate the increase in annual energy demands at major US airports with plausible growth trajectories of HEA technology. For a given BSED-MF, we switch a flight to HEA if its flight distances is within the range of its retrofitted hybrid electric variant. This step defines the size of the domestic fleet that gets electrified.

![Graphs showing annual demand for various airports under different BSED-MF combinations.](image)

Figure 1 plots the projected increase in aggregate annual electricity demands at six large airports in the United States—Hartsfield-Jackson Atlanta International Airport (ATL), Chicago O’Hare International Airport (ORD), Dallas/Fort Worth International Airport (DFW), Dulles International Airport near Washington D.C. (IAD) and San Francisco International Airport (SFO). In this study, we consider BSED and MF values that are deemed feasible in the 2030-2050 time-frame, according to Bradley and Droney [11, 12], Pornet et al. [13], National Academies of Sciences Engineering and Medicine [3], Delhaye and Rostek [14] and Friedrich and Robertson [15]. The plots reveal that even moderate BSED and MF values for HEA will lead to a substantial annual battery energy consumption.

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For BSED below 700 Wh/kg, MF ≥50% is deemed impractical to use for any flight distance.
To illustrate the magnitude of that increase, notice that aggregate energy demand of SFO in 2018 was 311 GWh, according to the DataSanFrancisco program. Figure 1d confirms that electrification at SFO with any BSED-MF combination will substantially amplify said demand of 311 GWh. The phenomenon is similar for other airports. For example, ORD had an annual total energy demand of 441 GWh in 2002 according to the O’Hare Modernization Final Environmental Impact Statement. The projected increase in ORD will more than double that requirement even at BSED = 700 Wh/kg and MF = 25%. We ignore the possibility that an HEA may need to charge enough to complete a round-trip journey from and to that airport if the destination location lacks necessary charging infrastructure. Accounting for such possibilities will only increase our demand estimates.

![Figure 2: Frequency of flight distances for regional jets and single aisle aircraft flying out of ORD in 2018.](image)

For a given MF, one might expect total energy consumption from batteries on HEA to decrease with BSED, because one requires lighter batteries to deliver the same amount of power. However, that is not always the trend in Figure 1. To explain this apparent paradox, we plot the histograms of flight distances in Figure 2 served by regional jets and single aisle aircraft at ORD in 2018. Notice that the distance distribution of single-aisle aircraft is more right-skewed than that of regional jets. Higher BSED values allow larger travel distances. As a result, more single-aisle aircraft, traveling longer distances with higher energy needs, are converted to hybrid. Consequently, energy needs of HEA increase.

3. Peak Power Requirements and Peak Shaving Mechanisms

Grid infrastructure to deliver power at airports must be designed to cover daily peak power demands from HEA and the rest of the airport. In this section, we study the peaks from HEA charging at various airports.

Consider a naive charging scheme, where the energy requirement of HEA is delivered uniformly at constant power over its dwell-time at the airport. This power, summed
across all airplanes at each time yields the power requirement of HEA at the airport. In Figure 3, we plot the histograms of daily peak powers from HEA charging at SFO using the BTS dataset for 2018 under different BSED settings with MF = 12.5%. With BSED of 500, 700 and 1000 Wh/kg, we obtain median peak power demands of 25.8, 33.7 and 54.7 MW, respectively. The daily maxima are even higher, e.g., with BSED of 1000 Wh/kg, the highest daily peak is ∼82 MW. These demands are substantial, given that the average power demand of SFO in 2018 was 35 MW, according to the DataSanFrancisco program. Supporting grid infrastructure at the airports, including transformers and distribution lines must be sized to handle the power requirements of HEA. Peak powers from naive charging will pose steep requirements on the grid infrastructure. Even if transformers are properly sized, large peak demands typically increase power procurement costs manifold. This nonlinearity in the growth of procurement costs with peak demand arises due to the fact that generators committed to supply these infrequent peaks have much higher production costs than those used to supply base load. Smart coordinated charging among HEA can shave daily peak power demands.

3.1. Shaving Peak Power Demands

We now illustrate the potential of smart charging at airports to reduce daily peak power demands at airports. Assume for now that flight schedules remain the same, meaning that the arrival and the departure times for each flight are the same as those in the database from the US Department of Transportation’s Bureau of Transportation Statistics (BTS) [25]. Divide the day into $T = 1440$ one-minute intervals. We consider the charging of HEA fleet $F$, indexed by $n$. For aircraft $n$, let $t^A_n$ and $t^D_n$, respectively, denote its arrival and departure times at the airport gate. Define $E_n$ as its total energy needs for

Figure 3: Histogram of daily peak demands with different BESD and MFs at SFO. Here, (---) plots the histogram for BSED = 500 Wh/kg, MF = 12.5%; (- - -) plots BSED = 700 Wh/kg, MF = 12.5%; and (---) plots BSED = 1000 Wh/kg, MF = 12.5%; (---) plots BSED = 500 Wh/kg, MF = 25%; (---) plots BSED = 700 Wh/kg, MF = 25%.
the next flight leg. With $\gamma^t_n$ denoting the charging rate (power) drawn by HEA $n$ in period $t$, we formulate the smart charging problem as

$$\begin{align*}
\text{minimize} & \quad \sum_{t=0}^{T-1} \left( \sum_{n \in \mathcal{F}} \gamma^t_n \right)^2 , \\
\text{subject to} & \quad \sum_{t=0}^{T-1} \gamma^t_n \Delta t = E_n , \gamma^t_n = 0 \text{ for } t \notin [t^A_n, t^D_n] , n \in \mathcal{F} , \\
& \quad 0 \leq \gamma^t_n \leq Q_n
\end{align*}$$

over $\gamma^t_n$ for $n \in \mathcal{F}$ and $t = 0, \ldots, T - 1$. Here, $\Delta t$ equals 1 minute, the length of the interval. The first constraint enforces HEA $n$ to fulfill its charging obligations over its dwell-time. The second constraint imposes restrictions on charging rates allowed by the airplane battery and the power electronics. Charging power of a battery is often measured in terms of its C-rate. A power capacity of 1C implies that a battery requires one hour to fully charge it up to its capacity. We encode a 10C limit in $P_n$ for each flight, given that higher C-rates are deemed unrealistic (per Battery University [27]), treating the next flight’s energy requirement as the battery capacity. The objective function seeks to flatten aggregate charging profile within the constraints.

Table 3: Highest daily peak power demand in several airports with naive and smart charging.

<table>
<thead>
<tr>
<th>Airport</th>
<th>Number of flights being replaced</th>
<th>Highest peak (MW) under naive charging</th>
<th>Shaved peak (MW) under smart charging</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATL</td>
<td>212,205</td>
<td>194.5</td>
<td>98.5</td>
</tr>
<tr>
<td>ORD</td>
<td>158,991</td>
<td>138.7</td>
<td>63.5</td>
</tr>
<tr>
<td>DFW</td>
<td>103,177</td>
<td>94.3</td>
<td>38.9</td>
</tr>
<tr>
<td>SFO</td>
<td>66,737</td>
<td>60.3</td>
<td>25.2</td>
</tr>
<tr>
<td>IAD</td>
<td>35,085</td>
<td>55.1</td>
<td>27.1</td>
</tr>
<tr>
<td>SAN</td>
<td>20,876</td>
<td>30.3</td>
<td>14.6</td>
</tr>
</tbody>
</table>

Table 3 records the results from six airports for the days with the highest daily peaks from HEA charging under the naive uniform charging scheme using MF=25%, BSED=700 Wh/kg. The optimization is solved in Python with a Gurobi solver. The results illustrate that daily peaks can substantially reduce through smart charging.

Marginal alterations in flight schedules can further shave peak power demands. Even a latitude of 30-minutes in the flight departure times of a few flights can reduce daily peaks. For example, the highest daily peak of 55.1 MW for IAD under uniform charging can be reduced to 27.1 MW under smart charging.

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$^3$The energy requirement of a flight is upper bounded by the battery capacity. Encoding a C-rate constraint in $Q_n$ using that capacity ensures that our charging schedule always respects the physical charging rate constraints for batteries.
Figure 4: Charging profiles with naive uniform charging rate (---), smart charging (--), and smart charging with marginally altered flight schedules (---) at IAD on Dec 6, 2018.

reduces to 27.1 MW under smart charging; marginal flight schedule alteration reduces it further to 22.9 MW. Figure 4 plots the charging profiles under the three schemes.

4. Slot Allocation Model with HEA Charging

Our preliminary experiments in the previous section reveal that charging of HEA and scheduling of airplanes must account for the burdens of grid infrastructure upgrades required to support HEA. In this section, we formally explore a slot allocation problem that jointly optimizes schedules of all flights and charging profiles of HEA to abide by airport operational constraints and charging considerations. The slot allocation problem takes requested schedules from airlines at an airport as inputs and produces flight schedules as outputs. The established goal of this problem is the minimization of displacements of output schedules from requested schedules of flights in a way that limits congestion at runways and air-traffic (e.g., see Pyrgiotis and Odoni [20]) along with charging considerations of HEA within airline fleets.

Consider the slot allocation problem over \( T \) slots, denoted \( 0, \ldots, T - 1 \). Let \( S \) describe the slot requests within this horizon; each request is for departure or arrival of a flight in one among \( T \) time slots. Encode the slot requests in

\[
A^t_i := \begin{cases} 
1, & \text{if request } i \text{ must be fulfilled no earlier than slot } t, \\
0, & \text{otherwise}
\end{cases}
\]  

for \( t = 0, \ldots, T - 1 \) and \( i \in S \). The binary sequence \( (A^0_i, \ldots, A^{T-1}_i) \) assumes the form \((1, \ldots, 1, 0, \ldots, 0)\), where the position of the last unity indicates the slot to execute request \( i \). Akin to \( A^t_i \), define \( Y^t_i \) for \( i \in S \) and \( t = 0, \ldots, T - 1 \) that encodes the allocation decisions
instead of requests. That is,

\[ Y_t^i := \begin{cases} 1, & \text{if allocation } i \text{ is fulfilled no earlier than slot } t, \\ 0, & \text{otherwise} \end{cases} \]  

(3)

for \( t = 0, \ldots, T - 1 \) and \( i \in \mathcal{S} \). For meaningful allocations, we must have

\[ Y_t^i \geq Y_{t+1}^i, \quad Y_1^i = 1, \quad Y_t^i \in \{0, 1\} \]  

(4)

for all \( i \in \mathcal{S} \) and \( t = 0, \ldots, T - 1 \). These constraints imply that \( (Y_0^i, \ldots, Y_T^i) \) becomes a sequence of the form \((1, \ldots, 1, 0, \ldots, 0)\), where the position of the last unity describes the slot allocated to request \( i \). Runway capacity is typically limited and is described by the number \( R \) of arrivals and departures that an airport can handle within a horizon of \( L \) slots. Thus, we impose the constraint

\[ \sum_{i \in \mathcal{S}} \min\{t + L, T - 1\} \sum_{\tau = t}^{t+1} (Y_t^i - Y_{t+1}^i) \leq R \]  

(5)

for each \( t = 0, \ldots, T - 1 \).

Let \( \mathcal{C} \) describe the set of pairs \((j, j')\) of requests from \( \mathcal{S} \), where \( j \) is an arrival request and \( j' \) is the corresponding departure request. Then, we impose a lower bound \( W_{j,j'} \) on connecting times for flights at the airport as

\[ \sum_{t=0}^{T-1} (Y_j^{t+1} - Y_j^t) \geq W_{j,j'} \]  

(6)

for all \((j, j') \in \mathcal{C}\). We assume that all requests in \( \mathcal{S} \) are in arrival-departure pairs in \( \mathcal{C} \).

Let \( \mathcal{C}^H \) denote the subset of \( \mathcal{C} \) with requests of HEA. For \((j, j') \in \mathcal{C}^H\), let \( E_{j,j'} \) denote the total energy demand for the aircraft whose arrival/departure requests are indexed by \( j, j' \). Let \( \gamma_{j,j'}^t \) denote the charging rate during slot \( t \) for the battery of the aircraft that is identified by the requests \( j, j' \). The energy needs of that aircraft is enforced via

\[ \sum_{t=0}^{T-1} \left( Y_j^{t+1} - Y_j^t \right) \gamma_{j,j'}^t \Delta t = E_{j,j'}, \quad \gamma_{j,j'}^t \geq 0. \]  

(7)

Here, \( \Delta t \) is the length of the time slot. Such a constraint is enforced for all \((j, j') \in \mathcal{C}^H\). In addition, we impose two sets of constraints on the power delivered to the HEA. First, the aggregate power for charging all HEA across the airport is constrained by \( P \), the capacity defined by the grid infrastructure at the airport, as

\[ \sum_{(j,j') \in \mathcal{C}^H} (Y_j^{t+1} - Y_j^t) \gamma_{j,j'}^t \leq P \]  

(8)
for each $t = 0, \ldots, T-1$. Second, we enforce that charging rates for each individual battery does not exceed 10C. Specifically, we impose an upper bound $\overline{Q}_{j,j'}$ on the charging rate of the form

$$\gamma_{j,j'}^t \leq \overline{Q}_{j,j'}$$

for each $(j, j') \in C^H$ and $t = 0, \ldots, T - 1$. Similar to that in (1), we use the energy requirement of the flight as a proxy for the battery capacity to compute $\overline{Q}_{j,j'}$.

For a request $i \in S$, define its displacement as the positive (respectively, negative) difference $X_i^+$ (respectively, $X_i^-$) between the slot time allocated and the slot time requested, i.e.,

$$X_i^+ := \sum_{t=0}^{T-1} (1 - A_i^t) Y_i^t, \quad X_i^- := \sum_{t=0}^{T-1} A_i^t (1 - Y_i^t).$$

With this notation, we formally present the slot allocation problem as the following optimization problem.

$$\text{minimize} \quad \max_{i \in S} \max \left\{ X_i^+, X_i^- \right\} + \sum_{i \in S} (X_i^+ + X_i^-) + w \sum_{t=0}^{T-1} \left( \sum_{(j,j') \in C^H} \gamma_{j,j'}^t \right)^2,$$

subject to

4) for $i \in S, t = 0, \ldots, T - 1$,
5) for $t = 0, \ldots, T - 1$,
6) for $(j, j') \in C$,
7), 8) for $(j, j') \in C^H$,
9) for $(j, j') \in C^H, t = 0, \ldots, T - 1$,
10) for $i \in S$

over the variables $Y, \gamma$ and $X$. The objective function is a weighted combination of three terms. The first term is the maximum displacement. The second summand equals the total displacement over all flights. The third summand is a penalty that is designed in a way that minimizing it favors flat aggregate charging profiles of HEA across flights, similar in spirit to the smart charging problem in (1). The positive constant $w$ controls the trade-off between minimizing displacements and peak-shaving in charging the HEA. Assigning a low weight $w$ amounts to prioritizing the minimization of displacements of slot requests at the expense of higher peak powers required to charge the HEA. Note that while $P$ in (8) imposes a hard constraint on the total power drawn by HEA at the airport, the third term in the objective function with $w > 0$ seeks to additionally flatten the demand profile within these limits. $P$ encodes capacity constraints of the supporting grid infrastructure at the airport. Operating within these limits, peak shaving is crucial to minimize energy costs of airports. Sharp peaks in power demands are typically met with expensive generators, the added expense of which are levied on consumers. Given the magnitude of
the peak charging power requirements of airports due to HEA charging, electric peak demand charges can prove costly for airports. Airlines paying for such charges will likely pass on these costs to passengers, increasing travel costs. Positive $w$ can aid in flattening the power profile and reducing the peak power below $P$.

5. Case Study of Slot Allocation for the JFK Airport

We now conduct a representative case study for domestic flight operations at the JFK airport based on flight schedules on December 27, 2018. Specifically, we utilize the schedules of domestic flights from the BTS database for the JFK airport as the requested slots over the peak hours of 10:00-16:00, considering each slot to be 2 minutes in length. Per the BTS dataset, there were 215 slot requests during this time window. Among the requesting aircraft, 32 of them with 64 requests can be switched to the hybrid electric option, based on the selection criterion described in Section 2 with BSED of 700 Wh/kg and MF of 25%. According to the Federal Aviation Administration [28], JFK supports around 90 arrivals and departures per hour. Given that domestic flights account for roughly half the flights at JFK (see the report by The Port Authority of NY and NJ [29]), we consider a capacity of $R = 45$ over $L = 30$ slots for domestic flights. We encode a minimum connecting time of 30 minutes in $W$ for all aircraft. The problem in (11) is solved in Python with Gurobi.

Figure 5: Requested and allocated movements per hour at JFK airport on 12/27/2018; allocation decisions are based on the benchmark experiment that does not consider HEA charging.

First, we run a slot allocation problem without accounting for charging considerations. That is, we drop the constraints (7), (8) and (9) in the slot allocation problem (11) and set $w = 0$. In effect, we run an optimization problem only over the displacement variables $Y, X$. The outcome of this experiment serves as a benchmark to compare the subsequent results with charging considerations. Figure 5 illustrates that the resulting allocation decisions exhibit some displacements from requested schedules. Such displacements are inevitable, given that the peak hourly slot request exceeds our assumed runway capacity of $R = 45$. With the resulting slot allocation decisions, we construct a charging profile for HEA that will result from a uniform charging rate over their dwell times at the JFK air-
port. Charging HEA at a constant power level over the resulting allocations then yields a peak power demand of 35.9 MW.

(a) Histogram of positive slot displacements
(b) Charging profiles for HEA

Figure 6: Positive slot displacements and charging profiles for three different parameter sets: (1) Slot allocation without charging constraint under uniform charging (2) $\overline{P} = 20$ MW, $w = 0$, $\overline{Q} \sim 10C$ and (3) $\overline{P} = 20$ MW, $w = 1/\overline{P}^2$, $\overline{Q} \sim 10C$. For all experiments, $R$ is held constant at 45.

Next, we consider an upper bound of $\overline{P} = 20$ MW on the total power drawn by HEA at the JFK airport. This capacity is far less than the peak power of 35.9 MW obtained under a uniform charging schedule added to slot allocation that ignores charging considerations. Encoding a realistic 10C battery charging rate in $\overline{Q}$'s, we run the slot allocation problem with two different choices of $w$. With $w = 0$, we obtain a charging profile whose peak power is 20.0 MW, that equals the airport’s charging capacity. That is, even without explicitly seeking to flatten the aggregate charging profile across HEA via the objective, the optimization problem finds a slot allocation and charging schedule that respects charging capacity limits at the airport, enforced via (8). Even when the peak power respects said limits, it is useful to flatten the charging profile and reduce peak powers to avoid large peak demand charges. Upon choosing $w = 1/\overline{P}^2$, we obtain a charging profile whose peak power is 14.6 MW, that is even less than that obtained with $w = 0$. Thus, positive $w$ aids in peak shaving. This experiment reveals the complementary roles of $\overline{P}$ and $w$ in peak power management. The displacements from these experiments are visualized in Figure 6a and the charging profiles are plotted in Figure 6b. These figures demonstrate that charging considerations impact not only the charging schedules but they also affect the resulting flight schedules. In the same vein, changing the upper bound on the battery charging rate $\overline{Q}$ impacts both slot allocation decisions and charging profiles. Figures 7a and 7b capture this sentiment through an experiment with $\overline{P} = 20$ MW, $w = 1/\overline{P}^2$, $R = 45$, where $\overline{Q}$ encodes two different battery charging limits of 5C and 10C.

As one might expect, expanding the runway capacity to accommodate 50 flight movements instead of 45 movements per hour should reduce slot displacements. Indeed, aggregate displacements reduce non-linearly from 502 minutes with $R = 45$ to 206 minutes
Figure 7: Positive slot displacements and charging profiles with $P = 20$ MW, $w = 1/P^2$, $R = 45$ and two different choices for battery charging capacities: $Q \sim 10$C and $Q \sim 5$C.

with $R = 50$. Figure 8a confirms that the overall distribution of displacements skews leftward from this expanded runway capacity. This experiment utilizes $P = 20$ MW, $w = 1/P^2$ and $Q$ encodes a charging rate upper bound of 10C. Change in runway capacity from $R = 45$ to $R = 50$ not only alters the flight schedules, but it also changes the resulting charging profiles (see Figure 8b). The peak power changes from 14.6 to 16.0 MW. To explain this increase, note that an expanded runway capacity allows more arrivals and departures in each slot. As the throughput during peak hours increases, the aggregate power demand from the HEA during these peak hours concomitantly increases. This experiment illustrates that runway capacities not only impact flight schedules but also significantly affect the charging profiles and their peaks.

Our experiments demonstrate that constraints on airport capacities and slot alloc-
6. Conclusions and Future Directions

HEA technology is maturing fast. They are projected to become viable for commercial aviation over the next few decades. While their overall energy needs at a national scale had been estimated before, we took a much more nuanced view of airport operations with HEA in this paper. Specifically, we provided a framework to gauge the energy needs of operating a specific flight path with plausible hybrid electric options. This calculation allowed us to estimate the substantial increase in energy demands at major US airports with likely technology growth scenarios. We showed through various examples that one must carefully design the charging profile of HEA at airports to reduce peak power demands. Smart management of HEA charging profiles and slight alterations of flight schedules can help to significantly reduce peak power demands at airports. Such reductions can lighten the burdens of required grid infrastructure upgrades and allow airports to avoid peak electric demand charges. Building on this observation, we then proposed a slot allocation model that seeks to both minimize displacements of slots from requested schedules and flatten aggregate charging profiles. We illustrated our proposed formulation through a case study for JFK airport. The key insight from our analysis is that adoption of HEA within airline fleets will require coordination between flight scheduling and HEA charging. Scheduling and charging cannot be solved separately.

Our slot allocation model with HEA charging is designed for a single airport. Such a framework can be extended to jointly schedule flights and charge HEA across several airports. That framework will allow us to relax the requirement that each airport must fulfill the charging needs of all its outgoing flights. Rather, one can charge HEA at only a few airports that upgrade their grid infrastructure. We do not anticipate conceptual difficulties in formulating such a problem. However, solving such a optimization problem at scale will invariably require careful algorithm design. Note that our slot allocation model is meant as a planning tool that solves the problem prior to the date the flights are operated. Real-time contingencies inevitably require modifications of such plans. We plan to enhance our slot allocation model to include tactical recourse decisions that adapt to said contingencies. In this paper, we have not explicitly modeled the costs of HEA charging. In future work, we aim to study the design of contracts among electric utilities, airports and airlines to pay for powering HEA. Such a study will allow us to estimate how HEA adoption will impact flight ticket prices as such costs trickle down to passengers.
Appendix A. Characteristics of HEA Concepts

Table A.1: Battery energy usage $b_0$ in Wh per passenger-mile

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<th>Type</th>
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Table A.2: Maximum range of HEA in miles

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References


