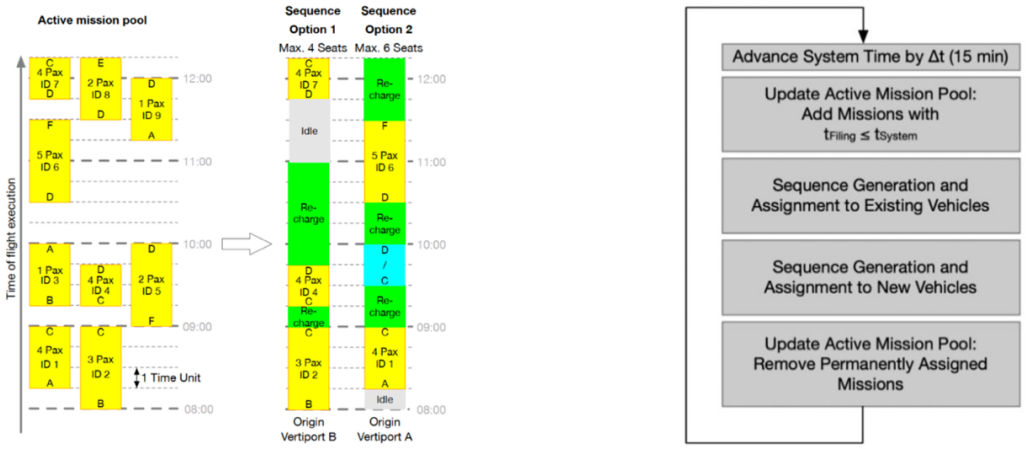
Abstract
Assessing the Operational Value of Booking Lead Time in Innovative Air Mobility Networks

Majed Swaid
German Aerospace Center (DLR), Institute of Air Transport, Hamburg

In Innovative Air Mobility (IAM), there are numerous use cases in which demand may arise spontaneously. This applies, for example, to private leisure travel or business travel, where the need to undertake a trip is known in advance, while the exact departure time within the day remains flexible. One of the key operational variables for describing spontaneous flight bookings is the booking lead time t_{BL}, defined as the time interval between the passenger's flight request and the desired departure. From the passenger's perspective, a short lead time is a direct indicator of high service quality and flexibility. From the operator's perspective, however, low values of t_{BL} may be disadvantageous, as they can restrict the efficient planning of vehicle rotations.
Building upon previous research, this contribution presents the results of the study described in [1], which was conducted within the IAM-OSA project to quantify the influence of booking lead time and, more broadly, the operational value of early information about future demand, on various aspects of fleet operations and ground infrastructure requirements. Assuming a constant transport performance, the minimum booking lead time is varied between 60 and 180 minutes. Subsequently, fleet size, fleet energy efficiency, temporal fleet utilization, and ground infrastructure requirements are quantified. In addition, both peak loads and daily average loads of the parking infrastructure are analyzed.



(a) (b)

Figure 1: (a) Schematic representation of vehicle operating plans. (b) Adapted rolling-horizon fleet planning workflow.

In [2], a method was presented that enables the estimation of fleet size and infrastructure requirements for predefined demand scenarios. To this end, a fleet is constructed by successively generating mission sequences from a pool of 2400 missions, each representing the operational schedule of a potential vehicle candidate within the fleet (see Figure 1 (a)). These sequences are generated iteratively, and the most favorable solutions are selected using a Mixed Integer Linear Program (MILP) until every mission in the pool has been assigned to exactly one vehicle according to a one-to-one allocation. The sequence generation process additionally ensures compliance with the operational schedules' energy- and time-related constraints while preventing the seat capacity of a vehicle from being exceeded.
In [1], the model was extended by a rolling horizon approach, as illustrated in Figure 1(b). For this purpose, an entire day of operations is simulated in time steps of 15 minutes. With each time step, the system time advances by 15 minutes, making additional mission bookings visible to the operator. As soon as the rolling horizon exceeds the booking time of a mission, which depends on t_{BL}, that mission is added to the active mission pool. Subsequently, a MILP is solved at each time step to assign all missions within the active pool. As new booking

information becomes available over time, missions may be assigned repeatedly to different vehicles. This process continues until a final assignment becomes necessary to initiate the operational preparations required for the execution of a mission.

t_{BL}	Fleet Vehicle Count	Fleet Seat Count	Peak Parking Demand	Mean Parking Demand
60	**358** (0.0%)	**1506** (0.0%)	**462** (0.0%)	**307** (0.0%)
90	**321** (-10.3%)	**1342** (-10.9%)	**443** (-4.1%)	**270** (-12.1%)
120	**297** (-17.0%)	**1256** (-16.6%)	**435** (-5.8%)	**245** (-20.2%)
150	**301** (-15.9%)	**1276** (-15.3%)	**445** (-3.7%)	**249** (-18.9%)
180	**298** (-16.8%)	**1294** (-14.1%)	**441** (-4.6%)	**245** (-20.2%)

Table 1: Fleet size (in terms of number of vehicles and total seat capacity) and cumulative parking demand across the vertiport network as a function of booking lead time t_{BL}.

In Table 1, the most important results are summarized. The case of t_{BL} = 60 minutes shown in the first row serves as the reference scenario. As the booking lead time increases, the number of vehicles required to serve the same transport demand can be reduced from 358 to 297 vehicles, corresponding to a reduction of 17%. At the same time, the total number of seats within the fleet decreases from 1,506 to 1,256, representing a reduction of 16.6%. No additional fleet size reduction potential can be observed for further increases in t_{BL}. The reduction in fleet size is primarily attributable to a decrease in vehicle idle time on the ground. The results indicate that the cumulative idle time can be reduced by 29% for t_{BL} = 120 minutes. However, operating the fleet reduced by 17% comes at the cost of a 5% increase in the distance flown by empty repositioning flights within the network, corresponding to a 3% increase in total energy demand.

The analysis of infrastructure utilization shows that, within the Hamburg network consisting of 20 vertiports, a peak parking demand of 462 parking positions occurs for t_{BL} = 60 minutes. For $t_{BL} \geq$ 120 minutes, the reduction in fleet size is accompanied by a corresponding reduction in parking demand. When the local peak demands across the network are aggregated, the required number of parking positions can be reduced from 462 to 435 (-5.8%) for t_{BL} = 120 minutes. With regard to the average parking demand over the course of the day, the cumulative number of required parking positions can be reduced by 20.2% for t_{BL} = 120 minutes.

The study demonstrates a significant dependency of the required fleet size, and consequently of the associated infrastructure requirements, on the booking lead time t_{BL}. While the fleet reduction potential reaches 17%, the associated costs in terms of increased energy demand (+3%) and additional distance flown by empty repositioning flights (+5%) remain comparatively low. Increasing the booking lead time therefore represents an interesting trade-off for operators, as the resulting operational benefits come at the expense of reduced service quality and flexibility for passengers.

Furthermore, the results quantify the considerable operational value of early information about future demand, as increasing t_{BL} represents only one possible means of obtaining such information. The results may also be used to evaluate alternative approaches for improving demand awareness, such as robust intraday demand forecasting methods. Such forecasting approaches could in the future be based on city-specific traffic patterns, historical operational data, and additional influencing factors such as weather conditions or special events to predict demand developments throughout the day with a high degree of confidence. In this way, a similar information gain could potentially be achieved without reducing service quality through longer booking lead times.

[1] Swaid, M., “Impact of Booking Lead Time on Fleet and Infrastructure in Urban Air Mobility”, 35th Congress of the International Council of the Aeronautical Sciences, ICAS 2026, September 13-18, Sydney, Australia, 2026.

[2] Swaid, M., Pertz, J., Niklaß, M., and Linke, F., “Optimized capacity allocation in a UAM vertiport network utilizing efficient ride matching,“ AIAA Aviation 2023 Forum, San Diego, California. 2023.

Biography
Speaker: Majed Swaid

Majed Swaid is a researcher at the German Aerospace Center (DLR). He studied mechanical engineering at Hamburg University of Technology, focusing on flight control systems. Since 2019, he has worked on operational concepts in urban air mobility and U-Space at DLR's Institute of Air Transport in Hamburg.

Contact: Majed.Swaid@dlr.de