Research Article

TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Transportation Research Record
2023, Vol. 2677(1) 76–92

DOI: 10.1177/03611981221098396
journals.sagepub.com/home/trr
SAGE

Factors Affecting Demand Consolidation in Urban Air Taxi Operation

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Abstract

Urban air taxi (UAT) is envisioned as a point-to-point, (nearly) on-demand, and per-seat operation of passenger-carrying urban air mobility (UAM) in its mature state. A high flight load factor has been identified as one of the influential components in the successful operation of UAT. However, the uncertainties in demand, aircraft technology, and concept of operations have raised doubts about the viability of UAT. This study examines the impacts of exogenous parameters, such as demand intensity, demand spread, and ground speed, in addition to design parameters, including aerial speed, maximum acceptable delay, and reservations on average load factor and rate of rejected requests. The dynamic and stochastic problem of UAT fleet operation is studied by implementing a dynamic framework that aims to provide a solution to the problem via a discrete-event simulation. The results highlight the significance of demand spread, ground speed, and maximum acceptable delay in demand consolidation. Therefore, to ensure a high aircraft load factor, the UAT operator should specify the maximum acceptable delay and reservation time window given the demand pattern and ground-based transportation in the network.

Keywords

aviation, urban air taxi, urban air mobility, planning and analysis, systems modeling, transportation supply

Introduction

With the vision of eco-friendly autonomous aircraft equipped with distributed electric propulsion (DEP) and efficient batteries that allow short charging or swapping time, urban air mobility (UAM) continues to generate much excitement. More than 200 concepts and partnerships have been announced for electric vertical take-off and landing (eVTOL) aircraft (*1*). Compared with helicopters, eVTOLs are four times quieter and 10 times less expensive (*2*). Benefitting from this revolutionary aircraft technology, the Advanced Air Mobility (AAM) initiative focuses on carrying cargo and passengers between urban, local, regional, and intraregional areas, while the UAM market, as a subset of AAM, aims to transfer passengers and goods within metropolitan areas (*3–5*).

The UAM Coordination and Assessment Team (UCAT) outlines six UAM maturity levels (UMLs) in three states: initial (UML1 and UML2), intermediate (UML3 and UML4), and mature (UML5 and UML6) (*6*). While UML1 represents late-stage certification testing and operational demonstrations in a limited environment, UML6 covers ubiquitous UAM operations with system-wide automated optimization. The UAM operational concept (OpsCon) for passenger-carrying operations commissioned by NASA specifies three use cases over three states: *Human-piloted Air Medical Transport* (initial state), *Intra-Metro Air Shuttle* (intermediate state), and *Ubiquitous Air Taxi* (mature state) (*7*).

Consequently, urban air taxi (UAT) is a ubiquitous on-demand per-seat service that transfers passengers in urban or suburban areas using groundbreaking eVTOL aircraft (*4*, *5*, *7*). UAT does not have fixed routes or regular schedules, distinguishing it from other use cases of passenger-carrying UAM such as *airport shuttle* or *air metro*, which are envisioned to operate on predetermined routes (*4*, *5*). UAT utilizes semi-autonomous or fully autonomous eVTOL aircraft with low noise, low operating costs, and passenger capacity of 1 to 4 passengers. The service is on-demand, but it would be possible to book a

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flight with advance notice. The UAT flights are shared, carrying one or two passengers on a typical flight (*7*).

Under an entirely unconstrained (i.e., best case) scenario, the total available market value of airport shuttles and air taxis in the United States is estimated to be USD 500 billion with 11 million daily trips, which corresponds to 20% of the daily work trips across the U.S. However, willingness-to-pay, availability of the infrastructure and their capacity, adverse weather, and limited operation hours could reduce this market to 55,000 daily trips (i.e., 0.1% of total daily work trips in the United States) with an estimated USD 2.5 billion market value in the near term (*4*). Meanwhile, Morgan Stanley projects that the global total addressable market of UAM will be USD 1.5 trillion by 2040 (*8*).

Nonetheless, some attributes of the UAT use case (e.g., flying 100 times per hour, serving only two passengers or a passenger group that are family members, landing near home) are perceived with the lowest positivity (*9*). Porsche Consulting has identified 16 barriers to the development of vertical mobility over five areas: hardware, service, infrastructure, regulation and law, and social acceptance (*1*). Intramodality, reliability, and operation costs constitute the three barriers faced in providing UAT service. The study highlights the importance of multimodal operations for air taxi and further argues that, unlike commercial flights, delays play a significant role in the success of UAM. Lastly, it suggests that pooling passengers, which hinges on sophisticated dispatching strategies, could reduce the operating costs. Similarly, Uber Elevate suggests that ridesharing economics is one of the three critical steps toward lowering costs (*10*).

Factors such as pricing, the number of UAT pads, UAT aircrafts' cruising speed, and access time, among others, could affect the UAT market (*2*). Since dominant players have yet to emerge in the passenger UAM market, these components are surrounded by uncertainties. To this end, the dynamic solution framework developed for UAT operations is utilized in this paper, and the impacts of design parameters and exogeneous information on the success of demand consolidation are examined using a discrete-event simulation (*11*). The outcomes shed light on the importance of design and exogenous parameters in the viability of the UAT business model and the eventual benefits to society resulting from travel time savings.

Background

Aside from the UAM market studies commissioned by NASA, and ConOps and OpsCons provided by NASA and FAA, some players from the industry, including Uber Elevate, eHang, Volocopter, and Boeing have presented their visions on passenger AAM and UAM operations (*3–5, 7, 12–15*). Additionally, the UAM studies in the literature cover aircraft technology, air traffic management, demand, infrastructure, and fleet operations (*16*). On-demand aerial fleet routing and scheduling problem falls under the umbrella of the *Vehicle Routing Problem with Pick-up and Delivery* (VRPPD), where goods should be picked up or dropped off at specific locations. *Dial-A-Flight Problems* (DAFPs) were introduced by the emergence of on-demand per-seat aerial service with capacity and weight constraints and time windows, where a passenger's itinerary may include intermediate stops to pick up or drop off other passengers (*17*). DAFPs have been used on the regional level to model air taxi operations and air safari planning (*17–19*).

On the other hand, *Fractional Aircraft Ownership Programs* (FAOPs) have led to on-demand per-aircraft models (*20*). Since FAOPs are operated per aircraft, the flights are not shared, and there is no intermediate stop and no need for capacity or weight constraints. Therefore, FAOP models can be seen as a variation of DAFP with no intermediate stop. Additionally, in FAOPs, all requests must be accommodated even at the cost of upgrading or chartering the aircraft, while in DAFPs, the operator could reject the requests.

In the context of passenger-carrying UAM, Rothfeld et al. utilize a rule-based policy for routing and scheduling of aircraft within an agent-based simulation framework and assign the nearest idle aircraft to the request (*21*). Ale-Ahmad and Mahmassani (*22*) propose *Capacitated Location-Allocation-Routing Problem with Time Windows* (CLARPTW) to model per-seat on-demand UAT fleet operations (*22*). Their proposed concept of operations includes flexible meeting points to consolidate the demand and, therefore, decrease the operating costs. The model supports acceptance and rejection decisions. The objective function is formulated as a generalized cost, which maximizes the revenue of the UAT operator while minimizing the operating costs, the loss of goodwill associated with rejected requests, and the passengers' delay. If the fleet of UAT aircraft has the capacity of one, CLARPTW is a variation of DAFP with no intermediate stop. In the following study, Ale-Ahmad and Mahmassani present a dynamic solution framework for the stochastic and dynamic problem of UAT fleet operation (*11*).

Lastly, travel time savings would make UAT a competitive mode compared with ground-based transportation (*23*). Booz Allen Hamilton's UAM market study finds no significant demand for mandatory (i.e., work-related) trips that take less than 30 min on the ground. Furthermore, most of the passenger UAM demand is captured for trips that are at least 45 min on the ground. Multiple market studies envision the minimum distance for passenger UAM trips would be around 10 mi (*5, 24*).

Antcliff et al. argue that access time (including boarding and deboarding), security checks, and delays are important factors in maximizing travel time savings (*25*). Table 1 summarizes the operational assumptions for passenger UAM in the literature.

UAT Problem Definition

The UAT operator provides a multimodal, (nearly) on-demand, and point-to-point service using a fleet of homogeneous UAT aircraft. The requests for UAT service arrive in real time within a short period ahead of their desired service time. When a request arrives, the origin, destination, desired pick-up and drop-off UAT pads, desired service time, and group size become known to the operator. Given the ubiquitous network of UAT pads, the origin and destination of a request coincide with the desired pick-up and drop-off UAT pads, respectively.

Each passenger group is willing to share a UAT aircraft with other passengers and is flexible about the location of their pick-up and drop-off UAT pads, which in turn enables the UAT operator to move the passengers on the ground within an acceptable distance to consolidate the customer requests and eliminate the unreasonably short empty flight legs. The itinerary of accepted requests constitutes origin, pick-up UAT pad, drop-off UAT pad, and destination. Therefore, this itinerary includes a maximum of two ground legs: one to ingress to the pick-up UAT pad and the other to egress from the drop-off UAT pad.

The UAT operator can reject a request if serving it is not profitable. However, to provide an equitable service, the UAT operator could include the loss of goodwill in its objectives. If the operator decides to serve a request, it guarantees a predetermined level of service. Therefore, the trip delay (i.e., deviation of the passengers' total trip time from their desired trip time) cannot exceed a prespecified value, which, in turn, limits the wait time for the aerial service, the ingress and egress time, and the deviation from the desired flight. When considering the acceptance of a new request, the operator cannot reject the requests that have been already accepted. However, the flight legs assigned to the accepted requests, and, therefore, the passengers' pick-up and drop-off UAT pads, could be modified as long as the passengers have not left their origin. After leaving the origin for the pick-up UAT pad, the pick-up UAT pad of the request is fixed, and only the drop-off UAT pad and boarding time of the assigned flight could be updated.

Dynamic Solution Framework

The UAT problem is presented as a dynamic and stochastic model. In practice, these models are often solved

Table 1. Operational Assumptions of Passenger Urban Air Taxi (UAM) in the Literature

Study	Cruise speed (mph)	Detour factor (%)	Boarding/ deboarding time (min)	Vertical ascend/ descend time (sec)	Ground speed (mph)	Max ingress/ egress	No. passenger seats	Shared flights	No. intermediate stops	Autonomy
Antcliff et al. (*25*)	120	NA	NA	114	21	0.66, 0.99 mi	1–2	Y	0	A, P
Holden and Goel (*12*) (Uber Elevate)	170	NA	3 (B), 2 (D)	60 (T) 75 (L)	NA	NA	NA	NA	0	NA
Porsche Consulting (*2*)	124	NA	3	NA	24.8	5 min	NA	NA	0	NA
Goyal et al. (*4*) (Booz Allen Hamilton)	125	5–15	3–5 (B), 2–3 (D)	NA	NA	NA	2–4	Y	0	P
Rothfeld et al. (*26*)	93	NA	≤ 2.5	50	NA	3.1 mi	2	NA	NA	NA
Rajendran and Zack (*27*)	170	NA	NA	NA	6	10 min	NA	NA	0	NA
Rajendran and Shulman (*28*)	160	NA	3 (B), 2 (D)	60 (T) 75 (L)	NA	NA	4	Y	0	NA
Ale-Ahmad and Mahmassani (*22*)	150	10	3 (B), 2 (D)	45 (T) 45 (L)	20	~10 min	1–4	Y	0	A

Note: A = autonomous; B = boarding; D = deboarding; L = landing; NA = not available; P = piloted; T = take-off; Y = yes.

as a sequence of static and deterministic models (i.e., snapshot problems). In addition to the dispatching strategy, which is devised in advance, four inputs are required to solve the snapshot problem at each decision epoch: requests, flight legs, UAT aircraft, and transportation network. The states of these inputs are dynamic and, therefore, should be repeatedly updated. The details of the dynamic solution framework for UAT fleet operation can be found in Ale-Ahmad and Mahmassani (*11*). A summary of the framework is presented in the following sections.

Customer Request

When request r arrives at time τ_r^{ARV}, its attributes are defined by the vector $\mathbb{A}_r^{REQ} = (\boldsymbol{O}_r, \boldsymbol{D}_r, \boldsymbol{S}_r^{DSRD}, \boldsymbol{E}_r^{DSRD}, q_r, \tau_r^{REQ})$, where τ_r^{ARV} the time request r arrives, $\boldsymbol{O}_r$ is the origin of request r, $\boldsymbol{D}_r$ is the destination of request r, $\boldsymbol{S}_r^{DSRD}$ is the desired pick-up UAT pad of request r, $\boldsymbol{E}_r^{DSRD}$ is the desired drop-off UAT pad of request r, q_r is the group size of request r, and τ_r^{REQ} is the requested time for service by request r.

In a ubiquitous network, $\boldsymbol{S}_r^{DSRD} = \boldsymbol{O}_r$ and $\boldsymbol{E}_r^{DSRD} = \boldsymbol{D}_r$ since the UAT pads are ubiquitously present in the space; however, the UAT model and operational policy presented in this study could be easily modified to address the problem in a network with a limited number of UAT pads. Additionally, Figure 1 illustrates temporal components associated with request r, where T_r^{ADV} is the advance reservation window for request r, which is specified by the difference between the arrival time of request r and its requested time (i.e., $T_r^{ADV} = \tau_r^{REQ} - \tau_r^{ARV}$); T_r^{DSRD} is the minimum trip time corresponding to the desired flight leg of request r (it is equal to the total trip time of request r when the trip starts immediately at τ_r^{REQ} and the passenger group of request r board the aircraft at their desired pick-up UAT pad and deboard at their desired drop-off UAT pad without ground-based transportation); T_r^{TRIP} is the total trip time of each passenger in request r, which includes ingress and egress time, aerial wait time, and aerial service time; $T_r^{TRIP} = \tau_r^{DST} - \tau_r^{REQ}$, where τ_r^{DST} is the time the passenger group of request r reaches its destination; T_r^{DELAY} is the total delay associated with request r, defined as the deviation of the trip time of request r from the desired trip time (i.e., $T_r^{DELAY} = T_r^{TRIP} - T_r^{DSRD}$); and ω is the maximum acceptable delay.

UAT Aircraft

The operator utilizes K aircraft for the aerial service. The static attributes of UAT aircraft k are represented by $\mathbb{A}_k^{eVTOL} = (Q_k, v_k^{air})$, where Q_k is the capacity of aircraft k (Q denotes the capacity of a homogenous fleet of aircraft), and v_k^{AIR} is the cruising speed of aircraft k (where v^{AIR} denotes the cruising speed of a homogeneous fleet of aircraft).

Flight Legs

Flight legs are the constituents of a UAT aircraft itinerary. In a *ubiquitous network* of UAT pads, where UAT pads are present all over the space, the desired pick-up and drop-off UAT pads of a request form a *desired flight leg*. Additionally, to eliminate the short repositioning flight legs, *connecting flight legs* are defined within Δ^{EMPTY} of the desired pick-up and drop-off UAT pads. Subsequently, c*andidate flight legs* are the union of desired and connecting flight legs. The static attributes $\mathbb{A}_i^{LEG} = (\boldsymbol{S}_i, \boldsymbol{E}_i, \tau_i^{MIN}, \tau_i^{MAX})$ of candidate flight leg i must be available to the UAT operator. $\boldsymbol{S}_i$ is the starting point of flight i, and $\boldsymbol{E}_i$ is the ending point of flight i. τ_i^{MIN} and τ_i^{MAX} are the earliest and latest times, respectively, that candidate flight leg i could start its service.

Transportation Network

The transportation network consists of ground and aerial networks. The ground network provides the travel times on the ground while the aerial network covers the

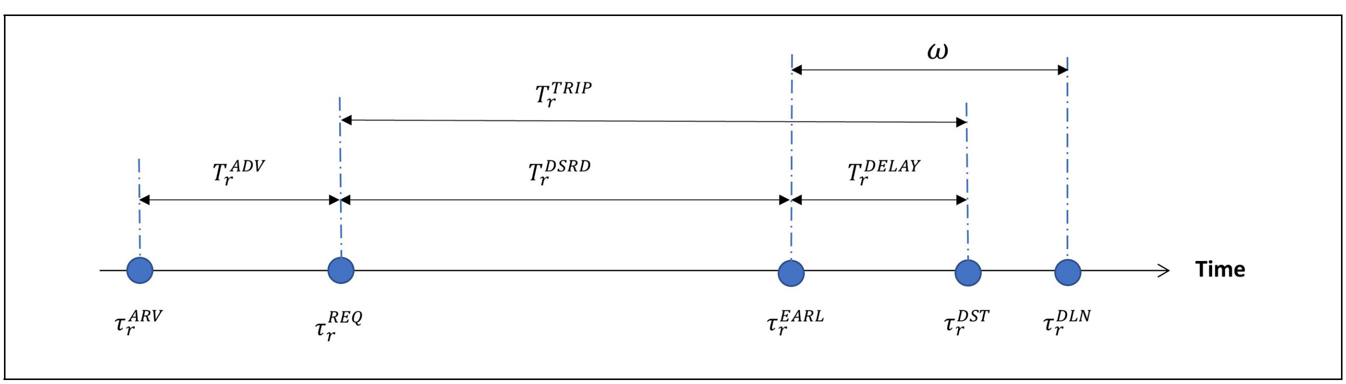

Figure 1. Depiction of temporal elements associated with request *r*.

information on the locations of UAT pads and, subsequently, the aerial travel times. The travel times could be deterministic or stochastic. In this paper, it is assumed that all travel times, either on the ground or in the air, are deterministic. The ground travel times could be estimated in multiple ways, including real-world data, traffic assignments, or average speed. In this paper, average speed over Euclidean distances is used to calculate the travel times on the ground.

Dispatching Policy

As new information, such as a new request, becomes available in a dynamic model, three methods could be used to adjust the solution (*25*). The first approach uses policies such as first-come-first-serve (FCFS) (*26*). The second method is a local heuristic search, where the static problem is solved at the beginning of the planning horizon using the information available to the analyst at the time. Subsequently, with the arrival of new requests, the solution is adjusted by employing heuristic methods such as insertion heuristics, deletion heuristics, or interchange (*27*). The third method is re-optimization, where the problem is re-optimized every time new information becomes available. Depending on the problem's size, degree of dynamism, and the time available for solving the problem, exact, approximate, or heuristic methods could be employed to update the solution with the new information.

The occurrence of an event (e.g., the arrival of a new request) could trigger the beginning of a decision epoch, or decision epochs could be scheduled at prespecified times (e.g., every 15 min). It is assumed that the decision epochs are determined exogenously, and they are scheduled every Δt^{UPDATE}. Furthermore, the dispatching policy presented in Ale-Ahmad and Mahmassani is used by re-optimizing the problem at each decision epoch (*11*). This policy, called *Capacitated Location-Allocation-Routing Problem with Time Windows and Short Repositioning Elimination* (CLARPTW-SRE), covers acceptance and rejection decisions, the allocation of requests to flight legs, demand consolidation, and the routing and scheduling of the fleet of UAT aircraft. Additionally, the aerial network is defined so that the short empty repositioning legs are eliminated. The following sections briefly explain the dispatching strategy.

Parameters

CLARPTW-SRE at time t is represented by a directed graph $\mathcal{G}_t = (\mathcal{N}_t, \mathcal{A}_t)$ with the set of nodes $\mathcal{N}_t$ and the set of arcs $\mathcal{A}_t$. The routing and scheduling part of the model resembles the ones presented in Yang et al. and Bertsimas et al. (*29*, *30*). The following sections briefly specify how the nodes, arcs, temporal parameters, and objectives are defined in the CLARPTW-SRE network.

Nodes. Let $\mathcal{N}_t^{REQ}$, $\mathcal{N}_t^{LEG}$, and $\mathcal{N}_t^{eVTOL} \subset \mathcal{N}_t$ denote the sets of candidate requests, candidate flight legs, and available UAT aircraft as of time t, respectively. $\mathcal{N}_t^{REQ} = \mathcal{N}_t^{UNASGN} \cup \mathcal{N}_t^{FLXSTRT} \cup \mathcal{N}_t^{FXDSTRT}$. $\mathcal{N}_t^{UNASGN} \subseteq \mathcal{N}_t^{REQ}$ presents the set of nodes associated with the unassigned requests. $\mathcal{N}_t^{FLXSTRT} \subseteq \mathcal{N}_t^{REQ}$ denotes the nodes related to the requests that were accepted in the previous decision epochs and, therefore, must be served, but their pick-up UAT pad is flexible. Similarly, $\mathcal{N}_t^{FXDSTRT} \subseteq \mathcal{N}_t^{REQ}$ denotes the nodes related to the requests that were accepted in the previous decision epochs and, therefore, must be served; however, these passengers have already left their origin, and their pick-up UAT pad is fixed.

Furthermore, let $\mathcal{N}_t^{LEG} \subset \mathcal{N}_t$ denote the set of nodes associated with flight legs available at time t to serve the requests. $\overline{\mathcal{N}_t^{E}} \subseteq \mathcal{N}_t^{LEG}$ defines a set of flight legs that do not end at the desired drop-off UAT pad of their intended request, implying that a flight leg should succeed $i \in \overline{\mathcal{N}_t^{E}}$. $\mathcal{N}_{it}^{SUCC} \subset \mathcal{N}_t^{LEG}$ is the set of nodes associated with succeeding flight legs of flight $i \in \overline{\mathcal{N}_t^{E}}$ as of time t, suggesting that flight leg i cannot be served unless one of the flight legs $j \in \mathcal{N}_{it}^{SUCC}$ is served. It is worth mentioning that $\overline{\mathcal{N}_t^{E}}$ and $\mathcal{N}_{it}^{SUCC}$ are two sets defined as part of network construction for short repositioning elimination. More details can be found in Ale-Ahmad and Mahmassani (*11*).

Arcs. Let $\mathcal{A}_t^{INIT}$, $\mathcal{A}_t^{SEQ}$, and $\mathcal{A}_t^{ALCT}$ represent the initial arcs from aircraft to flight legs, the sequencing arcs between flight legs, and the allocation arcs between requests and flight legs, respectively. Arc $(k, i) \in \mathcal{A}_t^{INIT}$ between aircraft k and flight leg i suggests that flight leg i could be served as the first flight on aircraft k's itinerary from its first availability UAT pad, while arc $(i,j) \in \mathcal{A}_t^{SEQ}$ between the nodes of flight leg i and flight leg j implies that candidate flight leg j could be potentially served after candidate flight leg i.

Lastly, an arc between request r and flight leg i indicates that candidate flight leg i could be assigned to request r. $\mathcal{A}_t^{INTND} \subseteq \mathcal{A}_t^{ALCT}$ denotes the set of (r, i) tuples where request r is the *intended request* of flight leg i. Each flight leg in a ubiquitous network is defined to serve their intended request. As a result, if an intended request of a flight leg is not assigned to it, the flight leg will not be served.

Times. The temporal parameters used in the dispatching strategy are defined as follows:

τ_r^{DLN} is the latest time the UAT operator guarantees the passengers of request r reach their destination (see Figure 1). In other words, $\tau_r^{DLN} = \tau_r^{REQ} + T_r^{DSRD} + \omega$;
τ_{rt}^{SRVC} is the earliest time that the UAT operator could start serving request r, defined as $\tau_{rt}^{SRVC} = \max\left(\tau_r^{REQ}, t\right)$ for $r \in \mathcal{N}_t^{UNASGN} \cup \mathcal{N}_t^{FLXSTRT}$ and $\tau_{rt}^{SRVC} = \bar{\tau}_r^{ORG}$ for $r \in \mathcal{N}_t^{FXDSTRT}$, where $\bar{\tau}_r^{ORG}$ is the time passenger group of request r left their origin;
τ_{kt}^{AVL} is the earliest time the itinerary of UAT aircraft k could be modified, and consequently, the time it becomes available for the future service as of time t. Furthermore, $\boldsymbol{L}_{kt}^{AVL}$ denotes the location of UAT aircraft k at τ_{kt}^{AVL};
τ_i^{MIN}, τ_i^{MAX} is the earliest and latest time, respectively, that flight leg i could be served;
T_{ri}^{INGR} is the ingress duration, defined as the total time for accessing the departure gate of flight leg i from the origin of request r;
T_{ri}^{EGR} is the egress duration, defined as the total time spent from the end of the deboarding of flight leg i until reaching the destination of request r;
T_i^{SRVEMP} is the time it takes to serve the empty flight leg i from its start to its completion;
T_i^{SRVREV} is the time it takes to serve the revenue-generating flight leg i from its start to its completion.

Additionally, T_{kit}^0 denotes the T_m^{SRVEMP} of flight leg m where aircraft k repositions from $\boldsymbol{L}_{kt}^{AVL}$ to the starting point of flight leg i. Similarly, T_{ij} denotes T_m^{SRVEMP} of flight leg m, which is the leg performed for repositioning a UAT aircraft from the ending point of flight leg i to the starting point of flight leg j. Lastly, ω is the maximum acceptable delay compared with the desired trip time.

Objective Function. The revenue earned by serving a request is proportional to the distance between the origin and destination of that request (i.e., D_r^{OD}) and its group size (i.e., q_r). $R_r = \alpha q_r D_r^{OD}$ denotes the revenue earned by serving the passenger group of request r, where α represents the revenue of providing the UAT service per mile per passenger. Moreover, the operator incurs a variable cost proportional to the aircraft travel mileage. $\bar{C}_{kit}^0$ is the total operating cost of serving revenue-generating flight leg i as of time t, which includes the preceding empty flight leg from $\boldsymbol{L}_{kt}^{AVL}$ to $\boldsymbol{S}_i$. $\bar{C}_{ij}$ is the total cost of serving revenue-generating flight leg j, including the preceding empty flight leg from $\boldsymbol{E}_i$ to $\boldsymbol{S}_j$. $\bar{C}_{kit}^0$ and $\bar{C}_{ij}$ are a function of the corresponding aerial mileage and β, which denotes the operating cost per mile.

Decision Variables

CLARPTW-SRE covers the location problem and the routing and scheduling problem simultaneously in a network without the short repositioning flight legs. The routing and scheduling part, specified through Equations 2 to 7, is adopted from the formulation with time constraints developed by Bertsimas et al. in an acyclic network (*30*). Following the notations in Bertsimas et al., let y_{ki} present a binary variable for $(k, i) \in \mathcal{A}_t^{INIT}$ (*30*). Its value is 1 if flight leg i is the first revenue-generating flight served by aircraft k from L_{kt}^{AVL}. Additionally, x_{ij} for $(i,j) \in \mathcal{A}_t^{SEQ}$ is 1 when revenue-generating flight leg j is served immediately after revenue-generating flight leg i, and 0 otherwise. Furthermore, p_i is a binary variable and is defined for $i \in \mathcal{N}_t^{LEG}$, where $p_i = 1$ implies that flight leg i will be conducted. Lastly, τ_i^{BOARD} is the time that flight leg i starts the boarding process. To allocate the requests to the flight legs, z_{ri} for $(r, i) \in \mathcal{A}_t^{ALCT}$ is defined as a binary variable, which takes the value of 1 when request r is assigned to flight leg i, 0 otherwise. It is worth noting that decision variables in CLARPTW-SRE, namely, y_{ki}, x_{ij}, p_i, z_{ri}, and τ_i^{BOARD}, have a temporal dimension since their values are determined at each decision epoch. However, for notational simplicity, the t index was dropped from the definition of these variables.

CLARPTW-SRE Formulation

The MIP formulation for CLARPTW-SRE given the state of the system at time t is presented as follows:

$$\max \sum_{r \in \mathcal{N}_t^{REQ}} R_r \left(\sum\nolimits_{i \in \mathcal{N}_t^{LEG}:(r,i) \in \mathcal{A}_t^{ALCT}} z_{ri} \right) - \left(\sum_{(k,i) \in \mathcal{A}_t^{INIT}} \bar{C}_{kit}^0 y_{ki} + \sum_{(i,j) \in \mathcal{A}_t^{SEQ}} \bar{C}_{ij} x_{ij} \right) \tag{1}$$

Subject to:

$$\sum\nolimits_{k \in \mathcal{N}_t^{eVTOL}:(k,i) \in \mathcal{A}_t^{INIT}} y_{ki} + \sum\nolimits_{j \in \mathcal{N}_t^{LEG}:(j,i) \in \mathcal{A}_t^{SEQ}} x_{ji} = p_i \ \forall i \in \mathcal{N}_t^{LEG} \tag{2}$$

$$\sum\nolimits_{i \in \mathcal{N}_t^{LEG}:(k,i) \in \mathcal{A}_t^{INIT}} y_{ki} \leqslant 1 \ \forall k \in \mathcal{N}_t^{eVTOL} \tag{3}$$

$$\sum\nolimits_{j \in \mathcal{N}_t^{LEG}:(i,j) \in \mathcal{A}_t^{SEQ}} x_{ij} \leqslant p_i \ \forall i \in \mathcal{N}_t^{LEG} \tag{4}$$

$$\tau_i^{BOARD} \geqslant \tau_i^{MIN} + (\tau_{kt}^{AVL} + T_{kit}^0 - \tau_i^{MIN})\, y_{ki} \ \forall (k,i) \in \mathcal{A}_t^{INIT} \tag{5}$$

$$\tau_j^{BOARD} - \tau_i^{BOARD} \geq \left(\tau_j^{MIN} - \tau_i^{MAX}\right) + \left(T_i^{SRVREV} + T_{ij} - \left(\tau_j^{MIN} - \tau_i^{MAX}\right)\right)x_{ij}\ \forall (i,j) \in \mathcal{A}_t^{SEQ} \tag{6}$$

$$\tau_i^{MIN} \leq \tau_i^{BOARD} \leq \tau_i^{MAX}\ \forall i \in \mathcal{N}_t^{LEG} \tag{7}$$

$$\sum\nolimits_{i\in\mathcal{N}_t^{LEG}:(r,i)\in\mathcal{A}_t^{ALCT}} z_{ri} \leq 1\ \forall r \in \mathcal{N}_t^{UNASGN} \tag{8}$$

$$\sum\nolimits_{i\in\mathcal{N}_t^{LEG}:(r,i)\in\mathcal{A}_t^{ALCT}} z_{ri} = 1\ \forall r \in \mathcal{N}_t^{FLXSTRT} \cup \mathcal{N}_t^{FXDSTRT} \tag{9}$$

$$z_{ri} \leq p_i\ \forall (r,i) \in \mathcal{A}_t^{ALCT} \tag{10}$$

$$p_i \leq z_{ri}\ \forall (r,i) \in \mathcal{A}_t^{INTND} \tag{11}$$

$$\sum\nolimits_{r\in\mathcal{N}_t^{REQ}:(r,i)\in\mathcal{A}_t^{ALCT}} q_r z_{ri} \leq Q\ \forall i \in \mathcal{N}_t^{LEG} \tag{12}$$

$$\tau_i^{BOARD} \geq (\tau_{rt}^{SRVC} + T_{ri}^{INGR})\ z_{ri}\ \forall (r,i) \in \mathcal{A}_t^{ALCT} \tag{13}$$

$$\tau_i^{BOARD} + T_i^{SRVREV} + T_{ri}^{EGR} \leq \tau_r^{DLN} + M(1 - z_{ri})\ \forall (r,i) \in \mathcal{A}_t^{ALCT} \tag{14}$$

$$p_i \leq \sum\nolimits_{j\in\mathcal{N}_{it}^{SUCC}} p_j\ \forall i \in \overline{\mathcal{N}_t^E} \tag{15}$$

$$p_i \in \{0,1\}\ \forall i \in \mathcal{N}_t^{LEG} \tag{16}$$

$$y_{ki} \in \{0,1\}\ \forall (k,i) \in \mathcal{A}_t^{INIT} \tag{17}$$

$$x_{ij} \in \{0,1\}\ \forall (i,j) \in \mathcal{A}_t^{SEQ} \tag{18}$$

$$z_{ri} \in \{0,1\}\ \forall (r,i) \in \mathcal{A}_t^{ALCT} \tag{19}$$

$$\tau_i^{BOARD} \geq 0\ \forall i \in \mathcal{N}_t^{LEG} \tag{20}$$

The maximization objective in Equation 1 includes revenue followed by (the negative of) variable costs of serving the flight legs. Equations 2 to 4 and 16 to 18 are the constraints that cover the routing. Equation 2 specifies that flight leg i is served only if it is the first flight on an aircraft route or it is served right after another flight. Equation 3 ensures that each aircraft serves at most one flight leg as the first flight leg on its route. Equation 4 suggests that a flight leg could be served right after flight leg i if only flight leg i is served itself.

Equations 5 to 7 address flight scheduling. Equation 5 ensures that if aircraft k had flight leg i as the first flight on its itinerary, the boarding time of flight leg i would be at least $\tau_{kt}^{AVL} + T_{kit}^{0}$. Equation 6 enforces that if flight leg j were served immediately after flight leg i, the boarding time of flight leg j should be at least equal to the boarding time of flight leg i plus the service time of revenue-generating flight i and the service time of the empty flight for repositioning the aircraft from the ending point of flight i to the starting point of flight j. Equation 7 specifies that the boarding time of flight leg i should be between the earliest and latest allowable boarding time for flight leg i.

Equations 8 to 12 cover the allocation part of the formulation and, therefore, assign requests to flight legs. Equation 8 ensures that each unassigned request is assigned to a flight leg at most once. Equation 9 covers the requests that were accepted in the previous decision epochs and, as a result, must be served. Equation 10 suggests that request r is assigned to flight leg i only if flight leg i is served. Equation 11 ensures that flight leg i must be served only if it could serve its intended request. Equation 12 is the aircraft capacity constraint.

Equations 13 and 14 cover the synchronization between the aerial and ground modes. Equation 13 indicates that flight leg i must start the boarding process after all the requests assigned to it have reached the departure gate. Equation 14 ensures that if request r is assigned to flight leg i, the boarding time of flight leg i should be such that the passenger group of request r arrives at their destination before the latest allowed time (i.e., τ_r^{DLN} in Figure 1). M is a big number and should be customized for $(r,i) \in \mathcal{A}_t^{ALCT}$.

Equation 15 explicitly specifies that if flight leg i ends at a UAT pad other than the desired drop-off UAT pad of its intended request (i.e., $i \in \overline{\mathcal{N}_t^E}$) to eliminate a short repositioning flight, one flight leg $j \in \mathcal{N}_{it}^{SUCC}$ starting at that UAT pad should be served to justify the relocation. Equations 16 to 19 are the binary constraints for the decision variables. Lastly, Equation 20 specifies that τ_i^{BOARD} is a positive real number.

Numerical Experiments

Even though some companies, such as BLADE Urban Air Mobility, currently offer air taxi service, on-demand and at-scale UAT operations using eVTOL technology is a conceptual system that does not exist (*31*). Simulation provides a tool for evaluating various strategies for the system's operation. *Discrete-event simulations* (DES) are well suited for modeling systems with complex queuing theory and resource allocation problems (*32*). This study uses DES to examine the impacts of various design and exogenous parameters on UAT fleet performance.

Experiment Design

When operating UAT, consolidating the requests is only possible if requests are sufficiently close. Therefore, the requests are generated in clusters to study the impacts of request consolidation. Each cluster represents a town or suburb of a metropolitan area. The centroids are located on the vertices of a square with the edges of length δ. Consequently, the network has 12 OD pairs with an average Euclidean distance of 1.138 δ.

Table 2. Values of Parameters Used in the Experiments

	$\mathcal{T}^{INT}$ (seconds)	σ (miles)	ν^{DRIVE} (mph)	ν^{AIR} (mph)	ω (minutes)	$\mathcal{T}^{ADV}$ (minutes)	α/β
Base values	**20**	**2**	**20**	**150**	**15**	**30**	**2**
Exogenous parameters							
Experiment 1	10, 15, **20**, 25, 30, 40	2	20	150	10	15	2
Experiment 2	20	1, **2**, 3, 4	20	150	10	15	2
Experiment 3	20	2	10, **20**, 30	150	10	15	2
Design parameters							
Experiment 4	20	2	20	100, 125, **150**, 175	10	15	2
Experiment 5	20	2	20	150	5, 10, **15**, 20	15	2
Experiment 6	20	2	20	150	10	1, 5, 10, 20, **30**, 40, 60	2
Experiment 7	20	2	20	150	10	15	1.2, 1.5, **2**, 2.5

Note: Values in bold denote the base values.

Let Δt^{UPDATE} denote the interval between two decision epochs. If new requests arrive within Δt^{UPDATE}, the problem will be re-optimized to update the current solution. The origin $\boldsymbol{O}_r$ and destination $\boldsymbol{D}_r$ of request r are randomly generated around the centroids using isotropic Gaussian distributions with the standard deviation of σ. Therefore, σ represents the spread of the demand around the centroids. The corresponding centroids of the request's origin and destination are randomly chosen from the four centroids. Let Δ^{OD} denote the minimum distance between the origin and destination of a request to qualify for a UAT trip. Consequently, the origin and destination of request r are generated so that the distance between origin and destination exceeds Δ^{OD} (i.e., $D_r^{OD} \geqslant \Delta^{OD}$). Furthermore, let Δ^{EMPTY} denote the minimum Euclidean distance to justify an empty repositioning flight leg.

The request arrival process is a Poisson process with the intensity of λ. Therefore, the interarrival times are exponentially distributed with the mean of $\mathcal{T}^{INT} = 1/\lambda$. τ_r^{REQ}; the requested service time for request r, is calculated as $\tau_r^{ARV} + T_r^{ADV}$, where T_r^{ADV} is randomly drawn from a uniform distribution with the mean of $\mathcal{T}^{ADV}/2$ and the range of $\left[0,\ \mathcal{T}^{ADV}\right]$. Lastly, it is assumed that the group size of each request is 1.

The fleet of UAT aircraft is homogenous, and, therefore, their capacity and speed are denoted by Q and ν^{AIR}, respectively. The initial location of aircraft k at time $t = 0$ (i.e., $\boldsymbol{L}_{k0}^{AVL}$) is randomly generated around the centroids using isotropic Gaussian distributions with the standard deviation of σ. Furthermore, it is assumed that all the aircraft are idle and available at the beginning of the planning horizon (i.e., $\tau_{k0}^{AVL} = 0$), and there is no incomplete flight leg on their itinerary.

The UAT operation is studied in a steady state when the performance measures have stabilized. However, the statistics are biased during the warm-up period since the system starts empty and idle. Therefore, to achieve statistically meaningful outputs, the planning horizon is set to 8 h. Subsequently, seven experiments are conducted: three related to the exogenous parameters and four covering the design parameters. Lastly, each experiment is replicated 20 times. Table 2 summarizes the parameters in each experiment.

The simulation framework is implemented in Python 3.7. The instances of CLARPTW-SRE are solved using the free academic license of Gurobi interface in Python, gurobipy 9.1, and on a machine with 3.00GHz Intel® Xeon® CPU and 128 GB RAM.

Parameter Settings

Let $\Delta t^{UPDATE} = 1$ min, $\Delta^{OD} = 10$ mi, and $\Delta^{EMPTY} = 1$ mi. Furthermore, the standard deviation of the isotropic Gaussian distribution, σ, is set to 2. The passengers will choose to walk if the assigned UAT pad is within $\Delta^{WALK} = 0.25$ mi (i.e., 5 min) of their origin or destination.

The driving speed over Euclidean distance, ν^{DRIVE}, is assumed 20 mph, implying that the driving speed in the network is greater than 20 mph since the on-ground routes rarely follow the Euclidean distance in the network. The time to reach the departure gate, including the security screening (i.e., T_{ri}^{DGATE}) and the time to reach the ground transportation area after landing (i.e., T_{ri}^{AGATE}), are assumed to be identical for all passengers and independent of the UAT port design. The values of T_{ri}^{DGATE} and T_{ri}^{AGATE} for $(r, i) \in \mathcal{A}_t^{ALCT}$ are set to 3 min and 2 min, respectively.

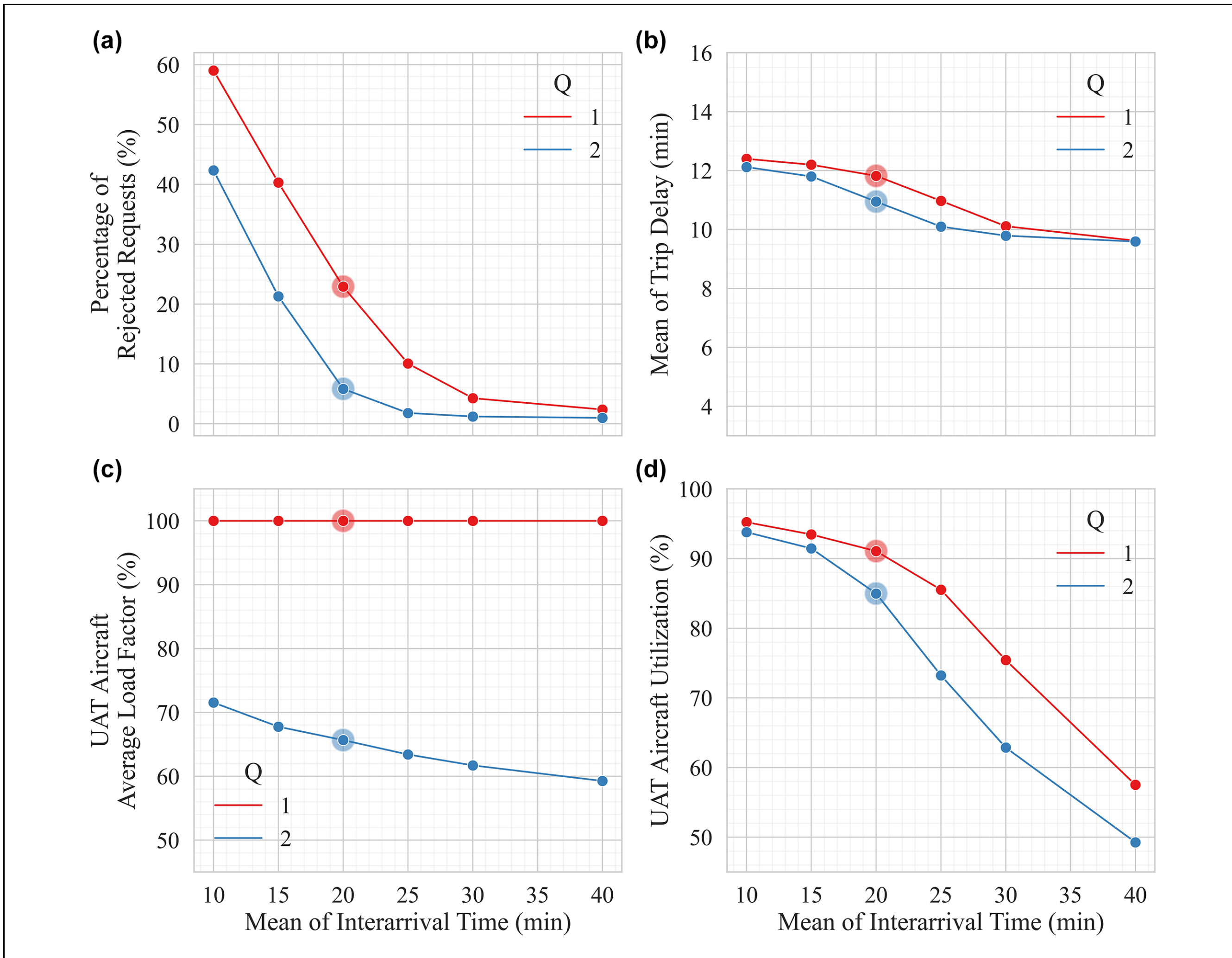

Figure 2. Sensitivity of performance measures to mean interarrival time ($\mathcal{T}^{INT}$) of 10, 15, 20, 25, 30, and 40 s for aircraft with capacities of 1 and 2. (*a*) percentage of rejected requests, (*b*) mean of trip delay in minutes, (*c*) UAT aircraft average load factor in percentage, and (*d*) UAT aircraft utilization in percentage.
Note: UAT = urban air taxi.

Multiple original equipment manufacturers (OEMs) have presented UAT aircraft designs with a cruise speed of at least 180 mph (*22*). Consequently, the aerial speed of 150 mph is chosen. The detour factor of the aerial trip is assumed 0.1, which is in the range of 0.5 to 0.15 suggested in another UAM study (*4*, *33*). The boarding and deboarding duration are set to 3 min and 2 min, the lowest values suggested in that study (*4*, *33*). Additionally, 30 s before departure and after landing are allocated for clearance. It is further assumed that it takes a UAT aircraft 45 s to ascend and 45 s to descend vertically. As a result, the overhead time of serving a flight leg, either empty or revenue-generating, comprises hover ascend and descend and ATC clearance before the take-off and after the landing, which amounts to 2.5 min. If the flight leg serves passengers, an additional 5 min will be added for passengers' boarding and deboarding. In summary, the overhead time of empty and revenue-generating flight legs are 2.5 min and 7.5 min, respectively.

Let $\delta = 30$ mi, and, therefore, the average trip would be 34.14 mi. Assuming an average driving speed of 30 mph over longer distances, an average trip would take 68.3 min with ground-based transportation. Additionally, the mean aerial distance would be 37.56 mi (i.e., 1.1×34.14). Therefore, the average time for serving a revenue-generating flight leg is 22.5 min (i.e., $\frac{37.56}{150} \times 60 + 7.5$). Furthermore, the average of 22.5 min for serving a revenue-generating flight would translate to the average trip time of 27.5 min for each passenger if there were no wait time for the aerial service and the requests were served without any ground-based transportation. Considering a maximum delay of $\omega = 15$ min, the minimum and maximum mean trip times for passengers are 27.5 min and 42.5 min, respectively. These numbers

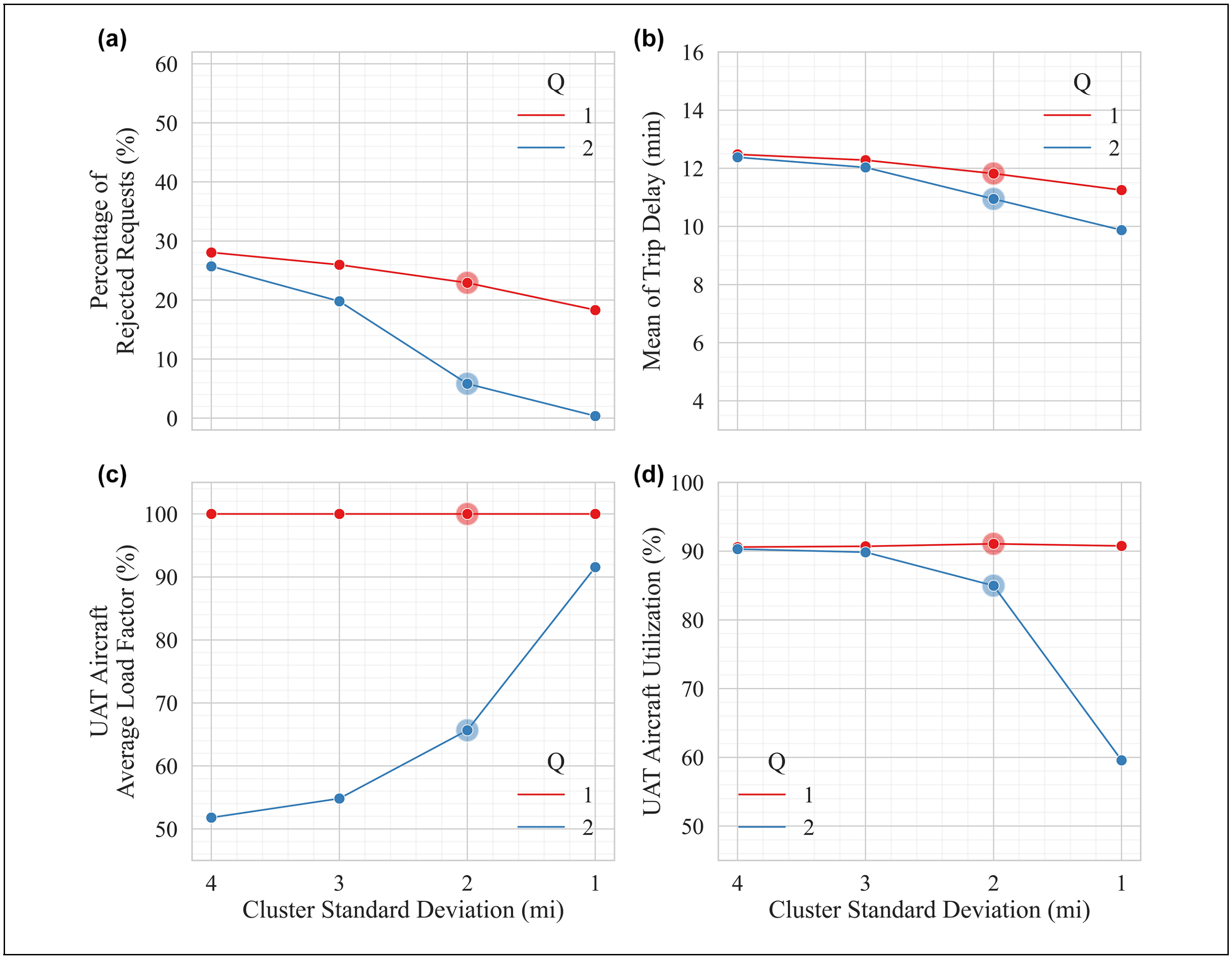

Figure 3. Sensitivity of performance measures to request spread (σ) of 1, 2, 3, and 4 mi for aircraft with capacities of 1 and 2. (*a*) percentage of rejected requests, (*b*) mean of trip delay in minutes, (*c*) UAT aircraft average load factor in percentage, and (*d*) UAT aircraft utilization in percentage.
Note: UAT = urban air taxi.

correspond to travel time savings of 37.7% to 59.7% compared with driving on the ground.

Lastly, the values of α and β are 2 and 1, respectively. $\alpha/\beta = 2$ implies that, roughly speaking, serving a request without air pooling is profitable as long as the repositioning mileage is shorter than the OD distance of the request.

Numerical Results

Experiment 1. Request Intensity ($\mathcal{T}^{INT}$)

With requests arriving more frequently, more opportunities are present for demand consolidation since more requests will have adjacent desired pick-up and drop-off UAT pads. In experiment E1, six levels of demand are examined (*30*): $\mathcal{T}^{INT} = 10$ s, where the demand is so high that more than 50% of requests are rejected; $\mathcal{T}^{INT} = 20$ s (base case), where the demand roughly meets the supply; and $\mathcal{T}^{INT} = 40$ s, where the demand is so low that aircraft utilization is around 50%. Figure 2*a* depicts how demand consolidation reduces the rejections by more than 15% at $\mathcal{T}^{INT} = 20$ s. Figure 2*c* illustrates how demand intensity could affect the number of shared flights and, therefore, the average load factor (i.e., capacity utilization). Even under the most intense demand, where more than 50% of requests are rejected, the average load factor is about 70% for two-seater aircraft. Figure 2*b* and *d* depict that, by lowering the aircraft utilization by more than 35 percentage points, the average delay would decrease by around 2 min.

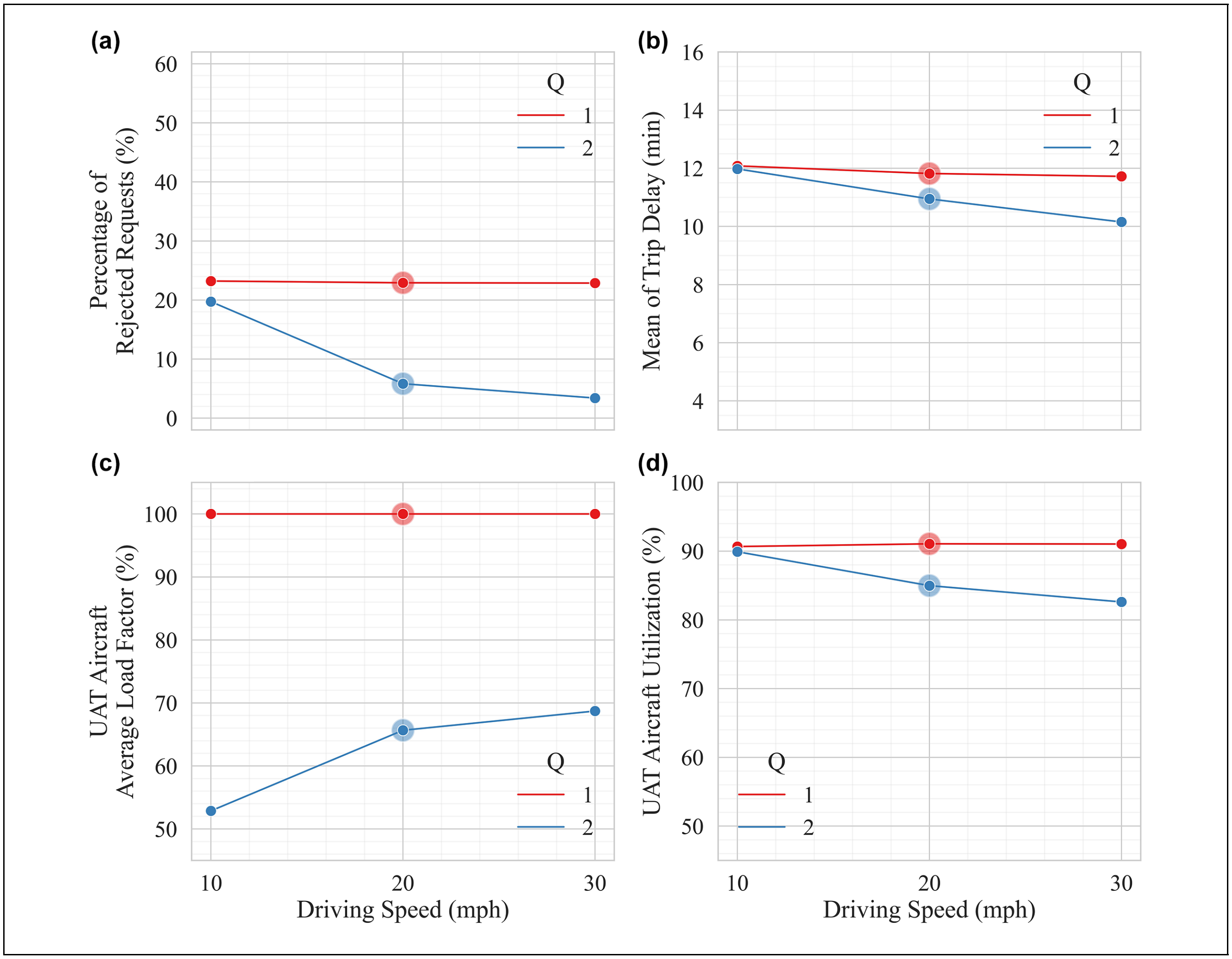

Figure 4. Sensitivity of performance measures to driving speed (ν^{DRIVE}) of 10, 20, and 30 mph for aircraft with capacities of 1 and 2. (*a*) percentage of rejected requests, (*b*) mean of trip delay in minutes, (*c*) UAT aircraft average load factor in percentage, and (*d*) UAT aircraft utilization in percentage.
Note: UAT = urban air taxi.

Experiment 2. Request Spread (σ)

The lower spread of requests increases the chance of demand consolidation. Figure 3 shows that with $\sigma = 4$, the average load factor is around 50%, implying nearly zero air pooling for a two-seater aircraft. Decreasing σ from 4 mi to 1 mi reduces the rejection of the request by nearly 10 percentage points in the aerial fleet with a capacity of 1. However, the noticeable benefit is seen for the capacity of 2. Figure 3*a, c*, and *d* highlight that the successful air pooling enabled by closely spread demand at $\sigma = 1$ would, respectively, decrease the rejection rate by nearly 25 percentage points, increase the average load factor by 40 percentage points, and decrease the aircraft utilization by 30 percentage points.

Experiment 3. Ground Speed (ν^{DRIVE})

The significance of driving speed of ingress and egress ground-based legs to demand consolidation is depicted in Figure 4. Decreasing the ground speed from 20 mph to 10 mph will lead to nearly no demand consolidation (i.e., the average load factor of nearly 50% in Figure 4*c*) since relocating the passengers on the ground is so slow that they cannot be moved while satisfying the maximum delay of $\omega = 15$ min. With the ground speed of 30 mph, the average load factor would increase to 70%, highlighting the importance of fast and reliable ground-based transportation in the success of the proposed UAT concept of operations with demand consolidation.

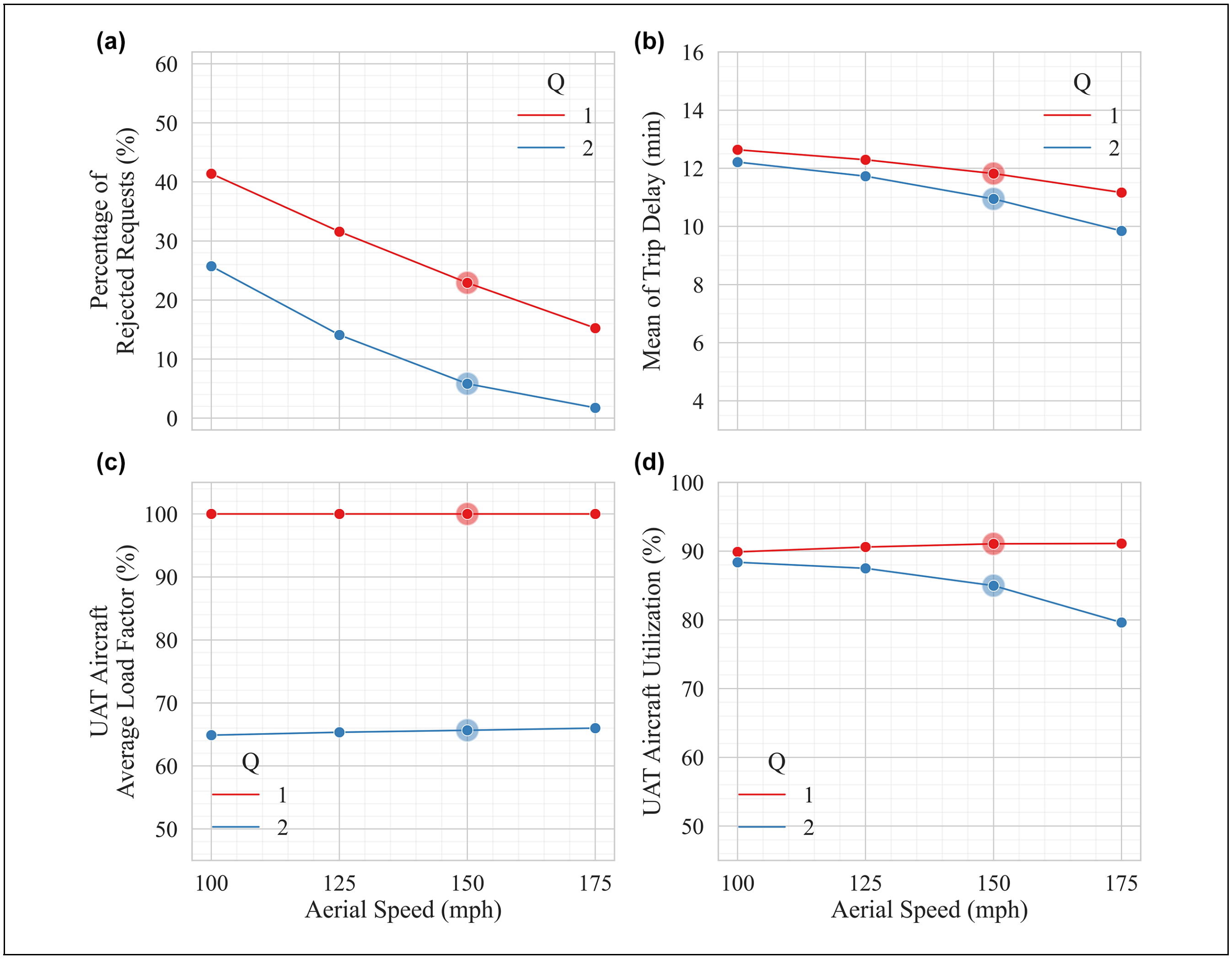

Figure 5. Sensitivity of performance measures to aerial speed (v^{AIR}) of 100, 125, 150, and 175 mph for aircraft with capacities of 1 and 2. (*a*) percentage of rejected requests, (*b*) mean of trip delay in minutes, (*c*) UAT aircraft average load factor in percentage, and (*d*) UAT aircraft utilization in percentage.
Note: UAT = urban air taxi.

Experiment 4. Aerial Speed (v^{AIR})

Figure 5 illustrates the impacts of aerial speed on the performance measures. The nearly parallel lines in Figure 5*a* suggest that the noticeable impact on reducing the rejection rate is not because of higher shared flights. As depicted in Figure 5*a*, the UAT operator could benefit from having an aerial fleet with a speed of 175 mph by serving more requests; however, the percentage of rejected requests would not get close to zero for $Q = 1$. Furthermore, the percentage of rejected requests with $v^{AIR} =$ 125 mph and $Q = 2$ is slightly lower than $v^{AIR} =$ 175 mph and $Q =$ 1, implying that demand consolidation provides an opportunity to avoid the complications of high-speed operations. Moreover, Figure 5*c* shows that increasing the aerial speed has minor impacts on the percentage of shared flights.

Experiment 5. Maximum Acceptable Delay (ω)

Increasing the maximum acceptable delay provides the UAT operator with more time to move the UAT aircraft to serve the requests. Additionally, the requests could be relocated to further distances on the ground to eliminate the short empty distances or consolidate the demand. Figure 6*a* shows that with ω = 5 min, 30% of the requests get rejected. However, increasing ω to 20 min in tandem with demand consolidation would decrease the rejection rate to 1%. Figure 6*c* shows that the load factor for ω = 5 min and $Q =$ 2 is almost 50%, suggesting

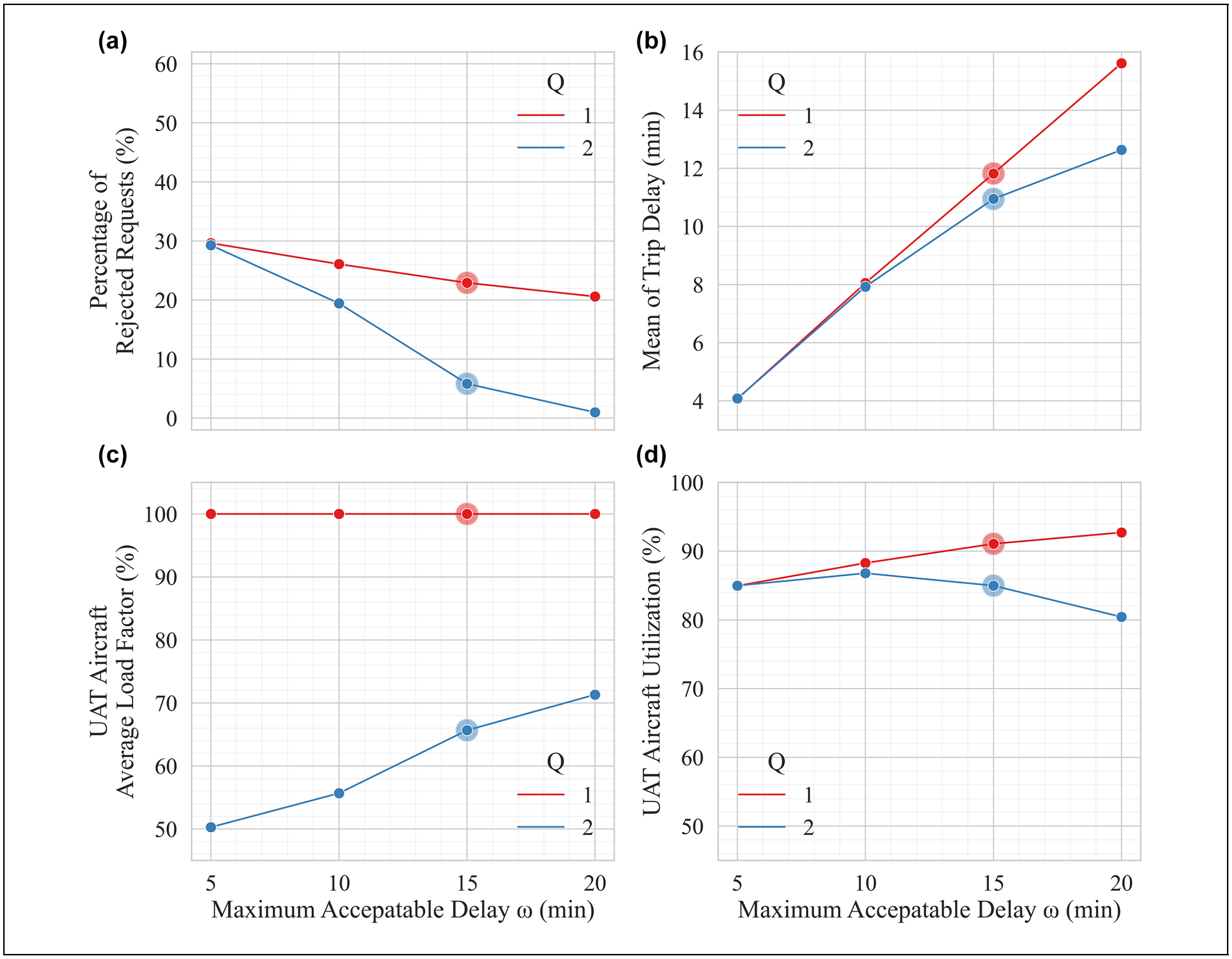

Figure 6. Sensitivity of performance measures to maximum acceptable delay (ω) of 5, 10, 15, and 20 min for aircraft with capacities of 1 and 2. (*a*) percentage of rejected requests, (*b*) mean of trip delay in minutes, (*c*) UAT aircraft average load factor in percentage, and (*d*) UAT aircraft utilization in percentage.
Note: UAT = urban air taxi.

that the maximum acceptable delay is too short for the requests to be relocated on the ground for demand consolidation. As ω increases to 20 min, the load factor increases to 70%.

Experiment 6. Maximum Reservation Time Window ($\mathcal{T}^{ADV}$)

When requests are known ahead of their desired service time, the operator has more opportunities for demand consolidation. Figure 7*a* shows that increasing the reservation time window has a diminishing benefit in reducing the number of rejected requests. As a result, the decrease in rejection rate between $\mathcal{T}^{ADV} = 30$ and $\mathcal{T}^{ADV} = 60$ is not significant. Providing the UAT operator with a reservation time window of 30 min could decrease the rejected requests by at least 8 percventage points compared with the case with immediate requests. Similarly, the average load factor increases nearly 6 percentage points, from 62% to 68%. Figure 7*b* highlights how increasing the reservation time window would decrease the average delay by almost 4 min, a 28% reduction in delay.

Experiment 7. Ratio of Revenue per Passenger Mile to Cost per Mile (α/β)

Figure 8 illustrates the impact of pricing on the performance measures. Considering the configuration of the synthetic network with the demand generated around four centroids on the vertices of a square, the value of $\alpha/\beta = 1.2$ would prevent the repositioning of the aircraft from one vertex to another to serve a request. Therefore,

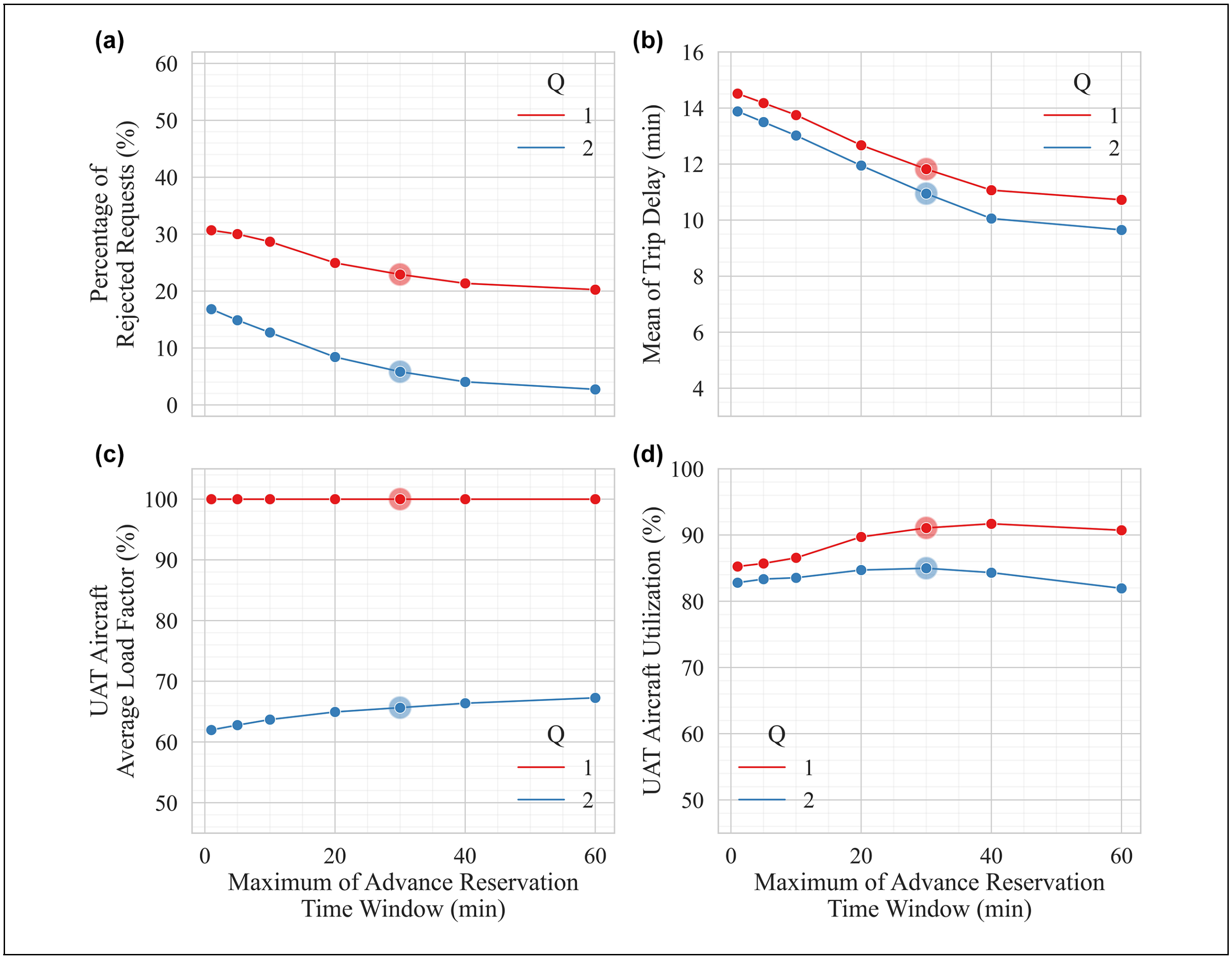

Figure 7. Sensitivity of performance measures to advance reservation window ($\mathcal{T}^{ADV}$) of 1, 5, 10, 20, 30, 40, and 60 min for aircraft with capacities of 1 and 2. (*a*) percentage of rejected requests, (*b*) mean of trip delay in minutes, (*c*) UAT aircraft average load factor in percentage, and (*d*) UAT aircraft utilization in percentage.
Note: UAT = urban air taxi.

the served requests are closer to each other, which provides more opportunities for demand consolidation. Figure 8*c* verifies that with an increase in α/β, the average load factor (for $Q = 2$) decreases. Additionally, the percentage of the rejected request is highest at $\alpha/\beta = 1.2$ with 27.2% for $Q = 1$ and 13.3% for $Q = 2$. Lastly, serving the nearby requests with $\alpha/\beta = 1.2$ has led to sinificant decrease in aircraft utilization.

Concluding Remarks

UAT is the envisioned use case of passenger UAM in its mature state. Given the ubiquitous operations of UAT, pooling the passengers and increasing the aircraft load factor is deemed as a critical step in the success of UAT operations. However, the absence of a dominant eVTOL aircraft technology and UAT operator feeds the uncertainty around UAM. To this end, the authors aim to study the impacts of various exogenous and design parameters on demand consolidation using a dynamic solution framework and an event-based discrete-event simulation.

To provide an acceptable level of service and meaningful travel time savings that warrant the choice of UAT, the operator guarantees to limit the delay incurred because of wait times and relocations. The results show that providing service with short delays while relocating passengers on the ground hinges on fast and reliable ground-based transportation. For the synthetic network used in this study, increasing the driving speed from 10 mph to 20 mph results in a 14-percentage-point increase in the average load factor. However, achieving

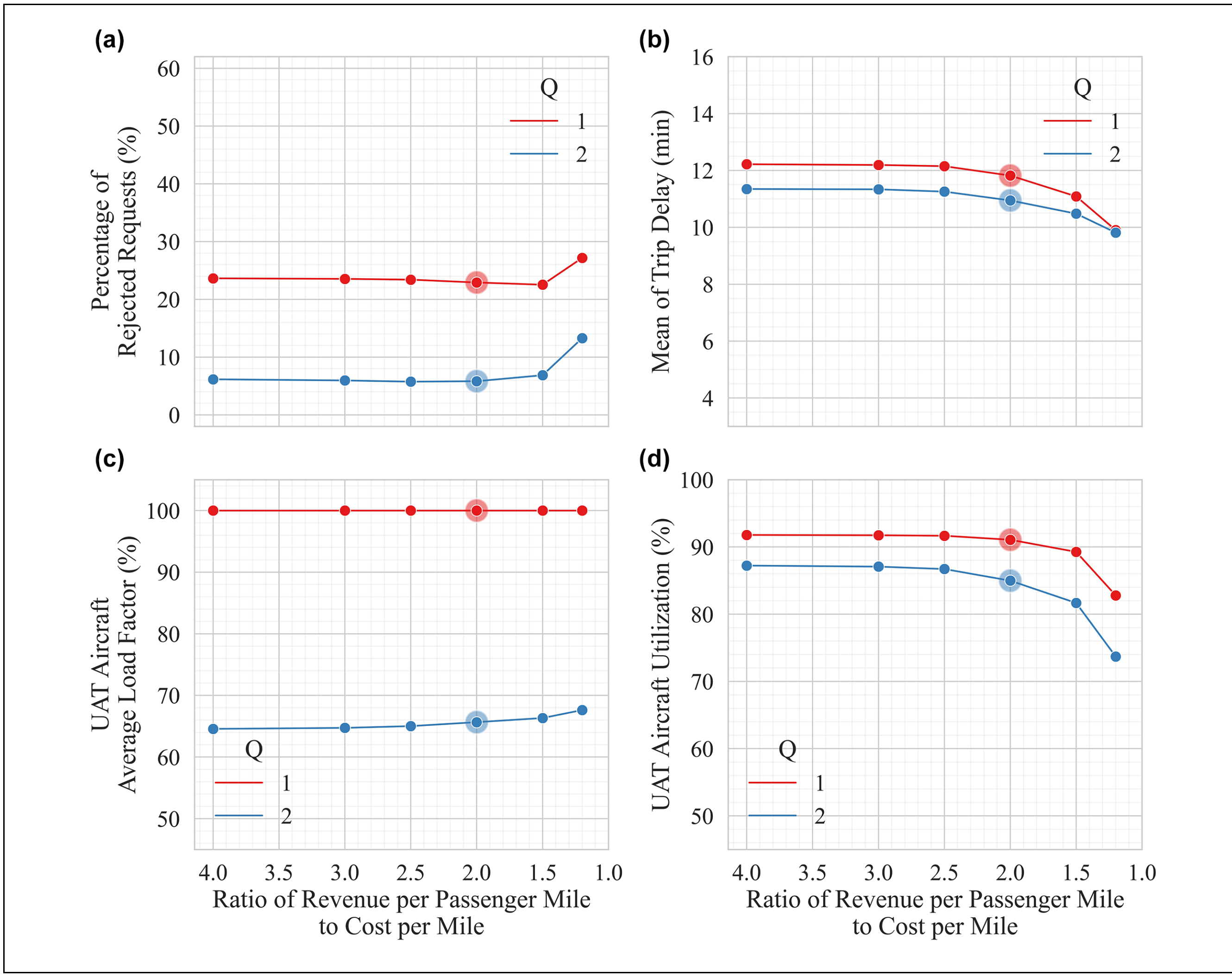

Figure 8. Sensitivity of performance measures to the ratio of revenue per passenger mile to cost per mile (α/β) of 1.2, 1.5, 2, 2.5, 3, and 4 for aircraft with capacities of 1 and 2. (*a*) percentage of rejected requests, (*b*) mean of trip delay in minutes, (*c*) UAT aircraft average load factor in percentage, and (*d*) UAT aircraft utilization in percentage.
Note: UAT = urban air taxi.

the ground speed of 20 mph over short distances might be challenging, particularly in downtown areas of a densely populated city. A study on travel time variability in Chicago using the data of Transportation Network Providers (TNPs), also known as Transportation Network Companies (TNCs), shows that the OD pairs with high travel time variability are primarily located in the downtown area and have an average distance of nearly 3 mi (*34*). Using the TNPs' data in Chicago, the average speed over Euclidean distances smaller than 3 mi is 9 mph.

Another significant factor in demand consolidation is the spread of the demand. For the given experiment with the driving speed of 20 mph and the maximum delay of 15 min, reducing the standard deviation of the Gaussian distribution of the requests around the centroids from 2 mi to 1 mi results in a 25-percentage-point increase in average load factor. Closely spread demand would result in the average load factor of 90%, which is well beyond the range of 50% to 80% estimated in another UAM study (*4*, *33*). Nonetheless, ground speed and demand spread, as the highly influential factors in demand consolidation, are exogenous information and are primarily beyond the control of the UAT operator. However, special attention should be given to these factors when selecting the passenger UAM market, particularly in the initial stages of the operation. Moreover, placing the UAM ports in locations that could provide a short and reliable ground access time to a dense and closely spread demand is another challenge facing the passenger-carrying UAM operations in the early stages. Locating the UAM ports near highways or a high-capacity public transit system could provide a high access speed or a high demand density; however, whether they can provide both is highly dependent on the specific UAM market under consideration.

Among the design parameters, aerial speed is an influential factor in reducing the rate of request rejection. However, it has minimal impacts on the demand consolidation and average load factor. The results suggest that a similar rejection rate could be achieved whether using high-speed aircraft with no demand consolidation or low-speed aircraft with demand consolidation, highlighting the value of demand consolidation in developing and selecting the aircraft technology.

Increasing the reservation time window and maximum acceptable delay decreases the rejection rate and increases the average load factor. However, when the maximum acceptable delay is long enough to allow the UAT operator to relocate the passengers on the ground for demand consolidation and move the UAT aircraft in the network to serve them, the UAT operator could immediately serve the requests with no advance notice required. For the synthetic network in this study, the rejection rate is almost zero for a maximum acceptable delay of 20 min, while with a maximum reservation time of 60 min, some requests could not be served. Consequently, the maximum acceptable delay has a noticeable impact on the average load factor. However, the maximum acceptable delay cannot be increased to the point that it diminishes the travel time savings.

In the CLARPTW-SRE formulation used in this study, the passenger delay is modeled as a soft constraint, and, therefore, the passengers' delay is not explicitly minimized. Consequently, even with aircraft utilization of 40%, the average delay is about 10 min per passenger. Furthermore, the results highlight how increasing the maximum of reservation time window from 1 min to 60 min would decrease the average delay by almost 4 min, a 28% reduction in delay.

The solution framework used in this study is based on deterministic travel times, while the stochasticity and reliability of the ground-based travel times play a critical role in the success of air pooling. Future studies should focus on the impacts of stochastic travel times on UAT aircraft average load factor. Furthermore, the findings of this study point to a high average load factor (i.e., 90%) when the requests are closely generated around the centroids. As a result, another study could compare the ubiquitous UAT operations with operations through limited UAM ports where demand is spread closely around those ports.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Haleh Ale-Ahmad and Hani S. Mahmassani; data collection: Haleh Ale-Ahmad and Hani S. Mahmassani; analysis and interpretation of results: Haleh Ale-Ahmad and Hani S. Mahmassani; draft manuscript preparation: Haleh Ale-Ahmad and Hani S. Mahmassani. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research is partially funded through a collaborative project with King Abdulaziz University of Science and Technology for joint work on "Autonomous Service Planning, Design and Real-Time Operation." Additional funding was provided through the Northwestern University Transportation Center.

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The authors remain responsible for all contents of this paper.