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Architecting urban air mobility airport shuttling systems with case studies: Atlanta, Los Angeles, and Dallas

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ABSTRACT

The purpose of this study is to define a holistic and effective architectural approach for implementing a safe and profitable pilot UAM airport shuttling system, which is extensible to the best available data at a given time. The proposition of this research is to leverage a system of autonomous UAVs capable of vertical takeoff and landing (VTOL) to transport passengers and cargo between airports and defined destinations in different urban cities in the United States: Atlanta, Los Angeles, and Dallas. The study comprises of defining a standard set of metrics to consider, developing a system model for defined case studies, and performing tradespace analyses to quantifiably evaluate alternative ways of achieving the most desirable architecture outcomes. This study models and evaluates 1,620 enumerable architectures and analyzes numerous tradespaces to examine the correlation and interrelationships between decision variables and performance metrics. Among the metrics, this analysis focuses on the interrelationships between Annual Profit, Mean Time Between Incident (MTBI), Upfront Cost, and Passengers Shuttled Per Day. The resulting analysis ranks architectures on the True and Fuzzy Pareto Front that is used to determine essential and quasi-necessary features in relation to these interrelationships. Based on the various stakeholders and their unique needs, the model recommends Los Angeles as the pilot city and for the system to leverage a FIFO queuing system, a smartphone interface, and a hybrid energy source that utilizes electric energy.

1. Introduction

Urban Air Mobility (UAM) started as a concept that was characterized by the National Aeronautics and Space Administration (NASA) as a technology that will ease traffic congestion in urban areas (Hamlett, 2017). The concept received significant attention from government institutions, as well as corporate and research communities, particularly as a potential solution to a growing population and the need for technologies that will ease the burden on transportation systems as well as the environment. In meeting these needs, UAM has the ability to disrupt the transportation industry and is expected to transform it in a dramatic fashion. UAM is a type of transportation service for low-altitude airspace which utilizes aircrafts, such as autonomous Unmanned Aerial Vehicles (UAVs), to transport passengers and cargo within metropolitan areas (Lascara et al., 2018). A UAM system consists of the following components: vehicles, command and control platforms, navigation and positioning systems and interfaces. Vehicles are expected to transport people

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and cargo within a specified area. A command and control platform is required to enable the transportation and the movement of UAVs by performing tasks to control the fleet, manage traffic, and ensure the safety of passengers.

There are many potential use cases for a safe and efficient UAM system, but one of the most commercially and technically viable solutions is as an airport shuttling service. In 2019, 780 million passengers were enplaned in the US and each flyer needed to find their way to an airport (Federal Aviation Administration, 2018). Peak days can mean the difference of a million additional passengers needing to get to a small number of locations around the same time. This problem is exacerbated even further in densely populated areas such as Los Angeles where driving a few miles on the highway during heavy traffic can take several hours (Vascik & Hansman, 2017b). Currently, there are a variety of existing ground transportation options such as driving a personal vehicle, using a ride-share service, taking a subway or rail service, or airport shuttle services that carry passengers and cargo from predefined locations to local airports. Although each of the options available today generally serve the purpose of transportation to a common place, each of them is burdened with issues ranging from reliability to environmental harm. The proposition of this research is to leverage a system of autonomous UAVs capable of vertical takeoff and landing (VTOL) to transport passengers and cargo between airports and defined destinations. VTOL enables fast take off and climb at steep altitudes, then decelerates to land vertically when reaching a destination. Ultimately, the objective of the system is to reduce ground traffic congestion around airports, decrease both pollutant emissions and public transportation strain, and lay the groundwork for expanded UAM operations.

In exploring the viability of such a system, one must understand the relationships among key design aspects including fleet management, infrastructure, traffic control, safety, user experience, financial viability, and technical performance. Because the UAM industry is still in its infancy, viable reference architectures are scarce (Crawley, 2016). Although system engineers working with UAM can examine similar, established transportation systems (e.g., shuttle buses, airport taxis), autonomous UAV operations in urban environments have not been widely implemented. The most significant technical challenges are UAV airworthiness (e.g., engine failure) and external factors (e.g., adverse weather conditions), while the most significant non-technical challenges are economic viability and federal Air Traffic Management regulations.

Our analysis does not focus on technical challenges associated with UAM, such as engine optimization, but instead focuses on trade studies related to the high-level architecture. For this reason, the model assumes that any technical challenges are addressed by the time the UAM system is implemented and that all viable technical solutions (e.g., gas-powered UAVs, electric-powered UAVs) are available for analysis. Specifically, this study aims to answer key questions surrounding the pilot implementation of such a system such as who are the key stakeholders and how do their needs compete, what metrics are most appropriate in considering a UAM-related trade study, what constraints exist within the system, what architecture proves most effective, and finally, what conclusions can be drawn from this analysis. As the initial implementation proves successful, additional analysis can be conducted to strategize the rollout across other unique urban ecosystems (e.g., phased, parallel, big bang, hybrid)."

The driving forces behind expanded UAV operations, including UAM, are the Federal Aviation Administration (FAA) and NASA. These agencies are jointly responsible for developing and enforcing federal UAV regulations, and also maintain purview over airport operations and national airspace. In addition to federal partners, this endeavor will require collaboration with industry partners (e.g., Boeing).

Increased interest in UAM has resulted in greater accessibility to a variety of publicly available data. This study leverages NASA market studies, university research, and UAM subject matter experts to ensure the system architecture analyses are rooted in a valid and extensive data set. Although this study achieves meaningful insights, and accessibility is rapidly expanding, it is worth noting the limitations in this domain. As opportunities grow in the commercial space around UAM, this data becomes more valuable and poses competitive advantage. Outside of that which is made publicly available by the government and through research, data is currently limited due to its proprietary nature which could prove meaningful to improving the fidelity of this analysis. The framework suggested however remains extensible to the opportunity of additional datasets or stakeholders. The overall objective of this study is to perform a rigorous analysis of UAM system architectures and lay the groundwork for future UAM system development.

2. Literature review

In a UAM Market Study published by NASA in November of 2018, UAM systems are analyzed for viability, including potential barriers and solutions (Goyal, 2018). The analysis focused on the three most challenging UAM use cases:

- Last-Mile Delivery: For rapid package delivery of items that are less than 5lbs from a distribution center to a receiving vessel
- Air Metro: Similar to the current public transportation mechanisms such as metro and buses with pre-determined routes and schedule
- Air Taxi: Allows people to call an air taxi which has a vertical takeoff and vertical landing capability to pick up people from their desired location and drop them off at their intended destination

The study found that there are several challenges for UAM implementation which include technical, physical, and operational integration of highly independent systems. There are also dependencies for the market to become viable. This includes safety and security, economics, demand, regulation, market substitutes and public acceptance.

Consulting firm McKinsey & Company conducted 200 expert and executive interviews, and surveyed 2000 consumers and business respondents on the topic of UAM (Hasan, 2018). Additionally, the market analysis includes data and research by academia, the public sector, and private sector. The analysis shows that UAM demand is driven by the target market, consumer willingness to pay, and technology availability. The target market was identified to be consumers living within the 15 largest metropolitan areas in the US and for the purposes of this study was segmented by age, income, and length of travel requirement. The consumer willingness to pay was shown to depend on key buying factors such as speed, comfort and price. The adoption of the new UAM technologies depends on the percentage of those consumers who value improved speed and who are open to autonomous air taxis, air metros, and Unmanned Aircraft Systems (UAS).

UAM is likely to be a commercially viable market with both parcel delivery and air metro use cases. The last-mile parcel delivery is projecting a potential profit by 2030 since there are e-commerce players who are working to improve the UAS delivery. Air metro could also be profitable 2030 if regulations are in place to accommodate it. Air Taxi is showing limited potential since high investment costs make a widespread air taxi market with ubiquitous vertiports unlikely in 2030. Places like Manhattan with people of high income and high traffic business shows potential where air taxi could be successful.

In addition to the prospect of demand and willingness, McKinsey & Company also examined public acceptance. They found that 25% of the consumers surveyed stated that they are comfortable with UAS. Another 25% reported that they will not use UAS when services become available. This indicates that only a fraction of the consumers are comfortable with the technology. The consumers concern falls into 5 categories which are: safety, privacy, job security, environmental threats, and noise and visual disruption. However, consumers also stated that with proven safety records and demonstrations, they would be comfortable with UAM. There are three strategies to address the concerns stated by the consumers:

- Investing in R&D such as key technologies to improve UAM adoption, noise abatement and safety systems and establishing safety through FAA coordination was shown to be key.
- Unified messaging campaigns is another strategy to increase public acceptance. This includes leveraging UAM partnerships between UAM stakeholders and emphasizing the benefits.
- Proactively engaging with concerned groups by identifying those groups that have resistance to UAM, holding forums to talk about UAM, and co-creating solutions to address these concerns.

The analysis includes a multitude of data from interviews and surveys with both businesses and consumers, but this survey data likely skews the study's outputs as consumer often misrepresent themselves in surveys. Furthermore, the study fails to explore other potentially viable construct for urban air mobility, such as servicing the areas surrounding an airport, and only evaluates air metro systems which function similarly to existing bus and subway systems. This study can serve as the baseline for further analysis which is rooted in quantitative data and considers a more focused and specific UAM system.

In the paper Systems Level Analysis of On-Demand Mobility for Aviation, published by MIT in 2017, they define On-Demand Mobility (ODM) as the concept of matching of transportation options (e.g., cars) with consumers in real-time, with the most prominent example being rideshare services such as Uber and Lyft (Vascik & Hansman, 2017a). The paper addresses the challenges associated with implementing an aircraft-based ODM system, including coordination with air traffic control, integrating UAS into airspace, and environmental factors such as noise.

It notes certain markets, such as Los Angeles, are plagued by significant transportation issues, with many transportation options becoming slower, less available, and more expensive each decade. This has driven increased demand for a market "disrupter", such as a safe and efficient ODM Aviation network.

The analysis explores the viability of ODM Aviation networks based on factors like technological readiness, regulations, market demand, and air traffic control. Researchers sought to answer three questions:

- Constraints: What are the critical technological, operational, regulatory, business or system interface factors that may constrain or prevent ODM Aviation implementation in the United States?
- Externalities: What externalities may originate from the proliferation of ODM Aviation networks in the United States? What potential impacts may they have on society, and how may they in turn influence ODM Aviation?
- Potential Mitigations: What technology or policy options may be considered in both the near and far-term to address the binding constraints and negative externalities of ODM Aviation implementation in the United States?"

As opposed to prior ODM research, this analysis considers a broader set of domains (e.g., business, regulations) to provide a more holistic systems-level analysis, then apply these insights to a dozen "reference missions" which represent potential use cases for an ODM Aviation system in Los Angeles.

These missions include Daily Commute, Point to Point, and Randomly Selected (with specific characteristics such as Wealthy Commuters and Mega Commuters), selected to improve the breadth of missions analyzed.

The analysis finds that there are a few potential early adopter markets including wealthy commuters, long-distance commuters, business executives, event attendees, emergency transportation, and vacationers. The study concludes by identifying constraints and challenges, delineating legal and regulatory considerations, and outlining potential approaches to mitigate these constraints.

This paper provides significant insight into the potential target markets for a UAM system and identifies constraints which prevent certain target markets, such as short-distance urban commuters, from being viable early adopters for a UAM system. Additionally, the study outlines some key considerations related to policy, regulatory, and integration. Although these considerations are not easily quantified, the analysis provides a framework for evaluating these qualitative factors and enables a more holistic understanding of the complexities associated with implementing a UAM system.

Many notable studies have investigated limitations and constraints of implementing UAM systems in populated areas. In Evaluation of Key Operational Constraints Affecting On-Demand Mobility for Aviation in the Los Angeles Basin: Ground Infrastructure, Air Traffic

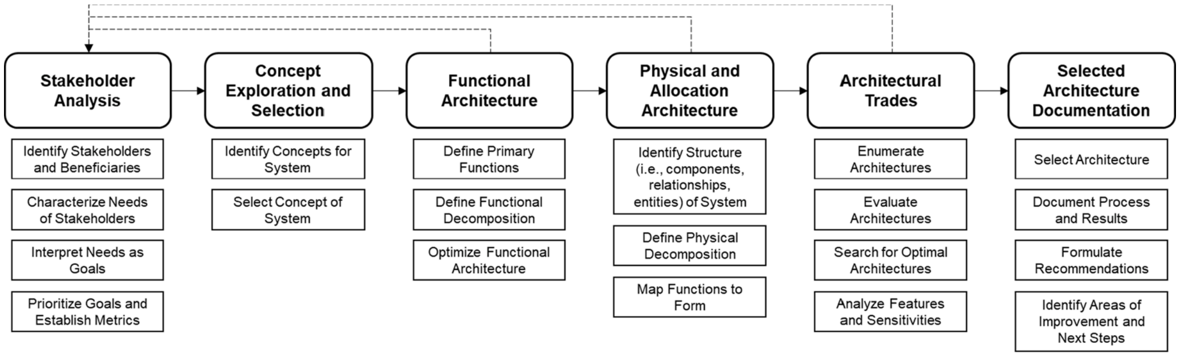

Fig. 1. Systems architecture process.

Control and Noise, these constraints are examined for causality, and where possible, mitigation tactics are evaluated for feasibility (Vascik & Hansman, 2017b). This study finds that the most significant constraints are related to infrastructure, the capabilities of air traffic control in low altitude with high density, and the public's acceptance of these systems due to noise. In the area of infrastructure, several challenges exist in placement of takeoff and landing areas (TOLA) such as limitations in aircraft performance and community acceptance of having these structures in the regions they live. Electric aircrafts, though still an emerging field, are observed to have the highest promise of mitigating these issues.

The examination of ASDE-X flight trajectory tracking data found that over 80% of operations utilized only 5% of the available low altitude air space, while air traffic control controlled 61% of the airspace. As a result, it is suggested as part of this study that the constraint of controlling air traffic could be mitigated through new approaches to airspace allocation which improve abilities to maximize flight densities. Aircraft noise on the other hand was found to be a wide-spanning issue with potential implications to where TOLAs can be built, the type of aircrafts used, and the overall demand for these systems. Two primary categories of mitigation techniques emerged when analyzing this problem: technology-based and operational-based. Technology-based mitigation includes advancement in aircraft technologies such as electric motors and distributed propulsion. Operational-based mitigation pertains to factors such as vertical ascent/landing, flight at higher altitudes, and generally avoiding communities during parts of flight operation which are known to be noisy.

These findings showcase the potential for UAM systems to be successfully adopted while mitigating disruption to the communities around them. Generally, it was found that for most constraints, effective mitigation measures exist. It is noted however that despite these promising advancements, an overarching issue remains in the way of the slow rate of regulatory response and collaboration. Until details of how to best regulate these systems and their expansion are instantiated, the development and deployment of UAM systems will remain slow to non-existent.

These existing UAM studies analyze a broad use case, such as ride share services, or evaluate a single hurdle of wide-scale UAM adoption, such as market viability. In contrast, this paper narrows its focus to a specific use case, which is a UAM system that delivers passengers and cargo to airports, and evaluates a broad set of measures of success to explore how system architecture decisions impact UAM system performance. This analysis references quantitative data from existing UAM studies where appropriate.

3. Methodology

Findings from the UAM studies in the previous section define the constraints, mitigation strategies, and viabilities of model development and analysis. These insights are reflected in how architecture decisions are delineated and assessed. This section walks through the architecture enumeration process, model structure, metric calculation process, and metric data sources.

3.1. System Architecture Process

The current state of practice for architecting complex systems commonly consists of document-centric systems engineering, where text-based descriptions are created and maintained throughout the life cycle project. Updating text-heavy documents requires system architects to make taxing downstream changes that result in major schedule delays. Decisions are typically made ad-hoc, where experts choose a handful of decisions and evaluate them with various degrees of analysis (Crawley, 2016). This approach lacks consistency, rigor in information capture, and is most vulnerable to human bias. While new developments such as the increasing adoption of SysML, a standard for model-based architecture description, have enhanced knowledge capture and improved communication among stakeholders, a large gap still exists in how to effectively handle complexity in resource constrained environments. To address this, the Systems Architecture Process shown in Fig. 1 is used in this study. This diagram illustrates the phases and activities required to formulate the high-level design of a UAM system to drive detailed design. This holistic, systematic, and iterative approach aims to address the associated complexity, ambiguity and unknowns through the consideration and selection of feasible and value-driven options, management of components and interfaces, prediction of emergent behaviors, and exploration of large architectural spaces.

The first four phases: Stakeholder Analysis, Concept Exploration, Functional Architecture, and Physical Allocation Architecture, set

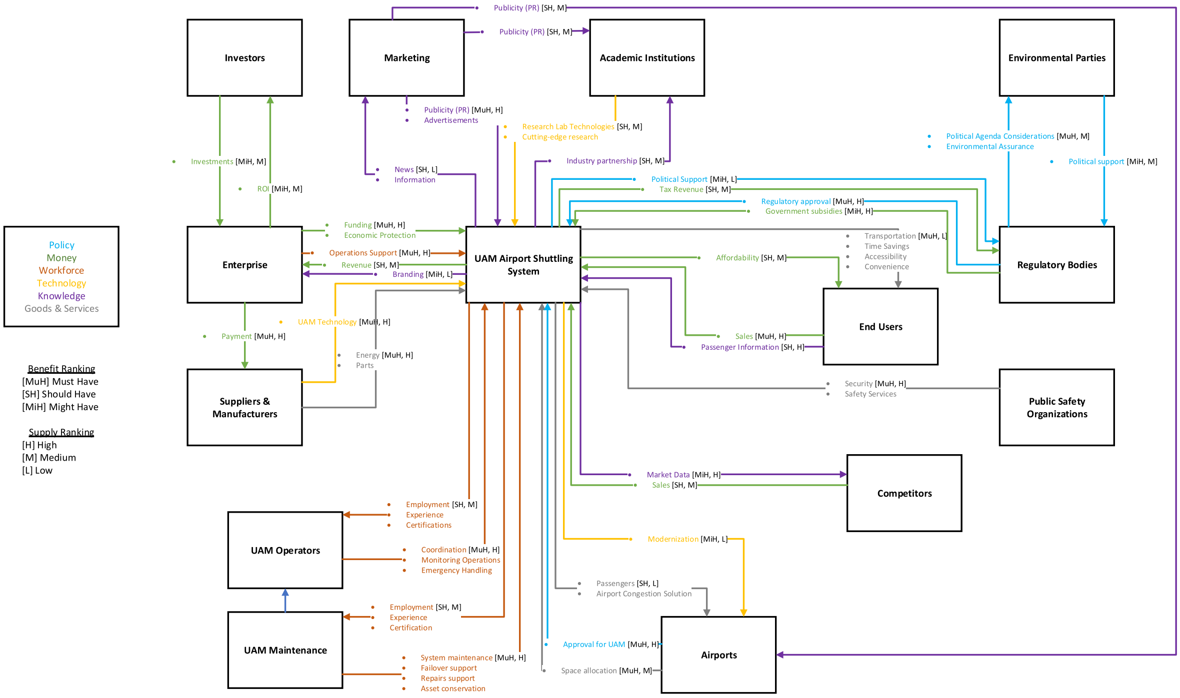

Fig. 2. Stakeholder value network.

Table 1
Stakeholder needs assessment.

Rank	Stakeholder	Goal Area(s)
1	Enterprise	Financial Viability, Safety, Performance, Infrastructure
2	End Users	User Experience, Safety, Financial Viability
3	Suppliers/Manufacturers	Infrastructure, Performance
4	Airports	Fleet Management, Infrastructure, Traffic Control
5	Regulatory Bodies	Safety, Financial Viability, Performance
6	Marketing	User Experience, Safety, Performance
7	UAM Operators	Fleet Management, Safety, Performance
8	UAM Maintenance	Fleet Management, Safety, Performance
9	Academic Institutions	Performance
10	Competitors	Financial Viability, User Experience

the foundation for identifying the most important decisions that have the largest influence on the needs of the stakeholders. These outputs serve as the basis for the model formulation, enumeration, evaluation, and trades analysis.

3.1.1. Stakeholder Analysis

The architecture of the UAM Airport Shuttling System was driven by stakeholder needs. While there were many potential individual stakeholders for the UAM Airport Shuttling System, only the top ten stakeholders were chosen from those identified in relevant technical and policy documents. This selection of stakeholder groups was determined based on perceived architectural impact. For example, stakeholders that did not seem to affect the architecture directly were excluded, while stakeholders that had similar impact were grouped together. The chosen level of abstraction for stakeholders helped provide more targeted analysis for identifying key relationships and outputs. A set of goals were derived from and aligned to the identified stakeholder needs. The goals can be summarized by seven topic areas: 1) Fleet Management, 2) Infrastructure, 3) Traffic Control, 4) Safety, 5) User Experience, 6) Financial Viability, and 7) Performance. The approximate returned value for the reference stakeholder, in Fig. 2, reveals the way in which value most effectively flows, enabling prioritization of stakeholders.

The needs for the respective stakeholders were characterized and quantified using a Stakeholder Value Network (SVN) as shown Fig. 2. The SVN identifies relationships between key stakeholders and qualitatively assigns both a benefit ranking, which rates how crucial the relationship is to each stakeholder, and a supply ranking, which rates how readily available each stakeholder is to the other. The SVN provides insight into which stakeholders are most significant among the set of stakeholders and identifies how certain stakeholders relate to each other. In later phases of the study, namely Architectural Trades, architectural decisions were chosen based on the ability of the system to deliver value and satisfy these stakeholder needs and derived goals (see Table 1).

Table 2
Example of initial brainstorming concepts.

Concept Description	
Generalization: High Efficiency, Low Speed Design Variables: Payload Capacity: Large Energy Source: Electric Aircraft Frame: Tiltrotor	Uses a combination of rotor and fixed-wing lift. The rotors are initially positioned vertically for takeoff/ landing and tilt forward until horizontal to enable wing-borne flight. The dual nature UAV is designed to carry a larger payload and is electric-powered.

Table 3
Morphological matrix of alternative architecture space.

ID	shortID	Decision	Units	Alt A	Alt B	Alt C	Alt D	Alt E
D_1	CI	Consumer Interface	none	Smartphone App	Website	Ticket Station		
D_2	QM	Queue Method	none	FIFO	Reservation	Ride Hailing		
D_3	MNP	Maximum Number of Passengers	passengers	1	2	3	4	5
D_4	ES	UAV Energy Source	none	Electric	Hydrogen Fuel	Gasoline	Gas-Electric Hybrid	
D_5	CS	City Selection	none	Atlanta	Dallas	Los Angeles		
D_6	SA	Speed of Aircraft	mph	100	150	180		

3.1.2. Concept Exploration and Selection

The Concept Exploration and Selection phase focused efforts on developing a high-level vision of the UAM Airport Shuttling System that guided the rest of the architecture process. Concepts were centered around the design of the Unmanned Aerial Vehicles (UAVs), the main component of the system. Design variables considered included the type of aircraft frame, energy source, and payload capacity. While initial generation methods resulted in a variety of concepts, the four that were ultimately selected were generalized to represent different levels of aircraft fuel efficiency (e.g., high, low) and speed (e.g., high, low), with an example shown in Table 2: Example of Initial Brainstorming Concepts. Each concept presents its own unique advantages and disadvantages in terms of cost, investment, materials, and maintenance. Specifying these alternatives provided a baseline for the functions and components that would be leveraged throughout the entire architecture process.

3.1.3. Functional Architecture

The functional architecture for the proposed UAM Airport Shuttling System consisted of three main views: the hierarchical decomposition, connectivity between internal functions, and the mapping between functions and goals. The functional architecture served as the projection of the complete architectural model of the UAM Airport Shuttling System in the functional space (Crawley, 2016). The overall purpose of the UAM Airport Shuttle system is to transport passengers between the airport and a designated location. The top-level function, Transport Passengers, was then further decomposed using a standard modeling language, SysML, to the following primary functions: transport passengers, load payload, takeoff UAV, etc. Each of the primary functions were decomposed into lower-level functions. For example, load payload included: queue passengers, load luggage, check aircraft weight. This was accomplished using a combination of techniques such as Hatley-Pirbhai, brainstorming, and similar system comparisons (e.g. bus shuttle system, airplane flight procedures) to determine the primary input and output processes and any necessary control and support processes. The value of the functional architecture validated whether the described functions that the system must perform satisfies the system and stakeholders goals as well as defining the relationships between functions. This was shown through the Goal-to-Function Domain Mapping Matrix, where each of the identified functions mapped to at least one or more of the goals from the Stakeholder Analysis phase.

3.1.4. Physical and Allocation Architecture

The physical and allocation architecture of the UAM Airport Shuttling System consists of a function to form mapping, definition of interfaces, and a concept of operations. Using Crawley's "2-down, 1-up" principle (Crawley, 2016), four sub-systems were identified: UAV, cargo, airspace, and infrastructure. Further decomposition was developed to provide a closer look at the components and expected interfaces. For example, the UAV sub-systems components included the power source, lift system, controls, navigation, and communications. A Design Structure Matrix was developed to define mechanical, electrical, fluid, and informational interfaces among the Airport Shuttle System components. The physical architecture served as the projection of the complete architectural model of the UAM Airport Shuttle System in the structural space by describing the components of the system that aggregate to produce a fully-functional system.

3.2. Model Structure

3.2.1. Architecture Enumeration

The model comprises of two major components: architecture decisions and metrics. Often, human-driven methods are utilized to make decisions, which results in a limited set of concepts and architectures being considered. To provide a robust analysis, an enumerable architecture model of the UAM system is created using the defined architecture decisions. The UAM architecture decisions

Table 4
Metrics-to-decisions matrix.

Metric	Decisions D_1	D_2	D_3	D_4	D_5	D_6
M1: Passengers Shuttled	X		X	X	X	X
M2: Integration Readiness Level	X	X	X	X	X	
M3: Mean Time Between Incidents		X	X	X	X	X
M4: Passenger Comfort Index	X	X	X	X	X	X
M5: Energy per Mile per Person			X	X		X
M6: Annual Profit	X		X	X	X	X
M7: Upfront Costs	X	X	X	X	X	X

are largely determined by comparisons between existing airport shuttling methods and identifying key elements in a full UAM system comprised of the UAV fleet, vertiports, and underlying infrastructure to provide transport to the customer. Table 3 shows the six decisions and their respective options.

The Consumer Interface (Decision 1) is the method in which passengers interface with the UAM system to get information and queue for transportation services, which serves as the cornerstone for determining the usability and intuitiveness of the system. The Queue Method (Decision 2) signifies how the UAM system matches operational UAVs to passengers, which is critical to determining how the UAV fleet will be managed and what customers can expect when waiting for service. The Maximum Number of Passengers (Decision 3) describes the total number of passengers that may be shuttled safely by the UAV, which has major impacts on UAV design, fleet management, and profit. The UAV Energy Source (Decision 4) represents the type of energy that will power the aircraft engine and digital functions onboard the UAV such as communications and display sub-systems. Environmental regulations and regulatory constraints on the UAV's carbon footprint and noise level will also vary among potential energy sources. The City Selection (Decision 5) determines where the entire UAM infrastructure will be designed, as city-specific characteristics, such as existing air traffic-related infrastructure and topography, pose unique advantages and disadvantages for UAM implementation. There may also be constraints on UAV design based on local and state regulations. Lastly, the Speed of the Aircraft (Decision 6) is the expected cruise speed for trips taken, which impacts the efficiency of fuel consumption, average trip durations, and optimal altitude for flight.

Each of the architecture decisions are designated as standard form canonical types, or decisions that have an individual discrete set of options. The unconstrained architecture space, A, is defined as the Cartesian product of all sets of allowed values (Knuth & Fuller, 2011).

For set of six architecture decisions $D = \{D_1, D_2, D_3, D_4, D_5, D_6)$

and the respective allowed values $m_1, m_2, \cdots, m_6$,

$$|A| = \prod_{i=1}^{6} m_i$$

Since only one option can be chosen for each decision, this results in an architecture space of 1,620. The architecture decisions are designed such that there are no logical constraints that all architectures are required to satisfy, so no architectures are discarded.

3.2.2. Architecture Evaluation

Following the architecture enumeration, the full model space is evaluated. This evaluation assesses the potential of each architecture to deliver a successful UAM system based on the combination of architecture decisions that each architecture represents. This is done by developing seven value functions which each represent a metric. The value function takes an architecture and its six decisions as an input and provides an estimate of the value of each metric as an output. The metrics used included: Passengers Shuttled per Day, Integration Readiness Level, Mean Time Between Incidents, Passenger Comfort Index, Energy Usage Rate, Profit per Flight, and Upfront Cost. These seven metrics are developed to be architecturally distinguishing, or able to identify differences in architectures. For example, the metrics depend on different combinations of decisions and thus yield different outputs in the tradespace as shown in Table 4. The formulas to calculate each metric are derived from data and research on the Uber Elevate Project (Uber Elevate, 2016) and the NASA UAM Study (Hasan, 2018), and currently available market and product data.

3.2.3. Passengers Shuttled per Day

Passengers Shuttled per Day represents the rate of ridership, with a more successful system achieving a higher value for this metric. As the UAM System caters to a larger rider base, its reputation as a legitimate mode of transportation may also improve.

Forecasting ridership using passenger boarding is a common methodology used among transit agencies and is done to predict ridership under a variety of scenarios (e.g., rerouting, extension of existing routes, etc.). Since this study requires the implementation of a new mode of transit, the most formal analytical technique called the Four Step Travel Model is used. This methodology comprises of evaluating how many trips are generated (Trip Generation), where trips go (Trip Distribution), what travel mode is used (Mode Choice), and what routes are taken (Trip Assignment). For this study, Trip Generation is calculated by the frequency of origins and destinations of trips that can be taken by the fleet where UAM is the primary transportation mode. Since this scenario uses pre-

Table 5
Metric 1 (Passengers Shuttled per Day) Variables.

Identifier	Long Name	Description
avg_trip_distance(CS)	Average Trip Distance	The average distance of a trip via UAV.
speed(MNP)	Aircraft Speed	The cruising speed of the UAV.
wait_time(CI)	Wait Time	The length of time (in minutes) a passenger is expected wait before their UAV is ready for flight.
refuel_time(ES)	Refuel Time	The length of time (in minutes) it takes to fully refuel an UAV.
refuel_distance(ES)	Refuel Distance	The number of miles a UAV can travel before needed to refuel.
fleet_size(CS)	Fleet Size	The number of UAVs in the UAM System.
passenger_size(MNP)	Passenger Size	The number of passengers an UAV can carry.
passenger_load(MNP)	Passenger Load	The average percentage of seats occupied in an UAV for trips taken.
takeoff_time	Takeoff Time	The length of time (in minutes) it takes for an UAV to takeoff.
board_time	Boarding Time	The length of time (in minutes) it takes for passengers to board their UAV.
hrs_of_operation	Hours of Operation	The length of time (in minutes) the airport has scheduled arrivals and departures.

determined starting and end ports, trip distribution and trip assignment are incorporated in the overall trip generation calculation as an average. Constant travel patterns across alternatives are assumed to remove excessive variability associated with the competition among transit modes. This metric also considers ridership potential associated with less tangible qualities (e.g., perceived comfort, convenience) for the consumer interface. While such characteristics can be subjective and are not easily quantifiable, studies have shown that there is a measurable difference in ridership for different transit technology characteristics (National Academies of Sciences, Engineering, and Medicine, 2006).

To calculate this metric, the decisions for Consumer Interface (Decision 1), Maximum Number of Passengers (Decision 3), UAV Energy Source (Decision 4), City Selection (Decision 5), and Aircraft Speed (Decision 6) must be assessed. The calculation is broken down into variables with the dependent decision capitalized, and constants as shown in Table 5. Sub-equations are organized in a logical ordering to understand how the metric was calculated. The quantitative effects for qualitative data associated with each decision can be found in 3.5 Quantitative Effects.

3.2.3.1. Calculate Duration of a Single Trip (DOSTL). The starting and ending nodes used for the average time required to complete a single trip can be defined as either from the moment they enter a designated vertiport to the moment they disembark the UAV once arrived at the airport or vice versa. To calculate this, the average trip distance is multiplied by the chosen cruising speed which accounts for unit conversion to minutes. However, due to unique geographical characteristics of each city, the average trip distance varies depending on the selected airport. Different consumer interfaces are associated with faster and slower processing times due to its ease of use and convenience. The added takeoff time and boarding time are constant and analogous to landing time and dismemberment time, respectively. This is represented by the coefficient, 2, before each constant.

$$DOSTL = avg\_trip\_distance(CS)*\left(\frac{60min}{speed(AS)}\right) + wait\_time(CI) + 2*tl\_time2*board\_time \tag{1}$$

3.2.3.2. Calculate Trips until Refuel (TUR). Time costs associated with refueling UAVs are also considered. Depending on the aircraft's energy source, the number of miles before a refuel is required varies. The associated mileage was divided by the average trip distance, which again is dependent on which city is selected.

$$TUR = \frac{refuel\_distance(ES)}{avg\_trip\_distance(CS)} \tag{2}$$

3.2.3.3. Calculate Trips per Day for a Single Aircraft (TPDSA). The TPDSA takes DOSTL and TUR to calculate the number of trips a single UAV can take in a day. Although airports are open 24/7, the hours of operation for potential UAM ridership is scoped to the hours that are generally associated with scheduled arrivals and departures (e.g., 5am to 12am). First, the number of UAV cycles are derived. Each cycle represents the number of trips possible until refueling is needed. This is calculated by dividing the hours of operation by the time associated with the trips until refuel and the time to refuel the aircraft. The total trips taken per day by a single aircraft is then multiplied by the number of trips in a cycle.

$$TPDSA = \frac{hrs\_of\_operation}{TUR*DOSTL + refuel\_time(ES)}*TUR \tag{3}$$

3.2.3.4. Calculate Trips per Day for the Fleet (TPDF). To calculate the trips taken by an entire fleet per day TPDSA is multiplied by the fleet size. The fleet size is dependent on the city selected since specific airports cater to a varying number of regions, neighborhoods, and/or counties. It is assumed that if an airport supports a smaller area, less UAVs and vertiports are needed for operations.

$$TPDF = TPDSA*fleet\_size(CS) \tag{4}$$

3.2.3.5. Metric Result: Calculate Passengers Shuttled per Day (PSPD). The final metric calculation takes the product of TPDF and the

Table 6
Metric 2 (Integration Readiness Level) Variables.

Identifier	Long Name	Description
ci_mult(CS, CI)	Consumer Interface Multiplier	The quantitative perceived advantage for the consumer interface selection.
pass_mult(CS, MNP)	Passenger Multiplier	The quantitative perceived advantage for the maximum number of passengers selection
energy_mult(CS, ES)	Energy Source Multiplier	The quantitative perceived advantage for the consumer interface selection.
queue_mult(QM)	Queue Method Multiplier	The quantitative perceived advantage for the consumer interface selection.
city_mult(CS)	City Selection Multiplier	The quantitative perceived advantage for the consumer interface selection.

number of passenger seats available on an aircraft. A passenger load was also considered, since it is unlikely that all seats on a given UAV are occupied for each flight taken.

$$PSPD = TPDF*passenger\_size(MNP))*passenger\_load(MNP) \tag{5}$$

3.2.4. Integration Readiness Level

The Integration Readiness Level assesses the initial maturity of an architecture for integrating an UAM system with existing infrastructure, processes, and conditions. Architectures that are evaluated for a higher readiness level are projected to have an advantage in aspects such as infrastructure development, air traffic coordination, and initial startup costs. The metric is calculated by the product of various decision multipliers that are defined in Table 6. Multipliers are quantitative and relative representations of the perceived gain for decision options. The multipliers for consumer interface, maximum number of passengers, and energy source decisions use two arguments since the benefit depends on a coupled relationship between decisions as shown in Table 6.

3.2.4.1. Metric Result: Calculate Integration Readiness Level

$$IRL = ci\_mult(CS, CI)*pass\_mult(CS, MNP)*energy\_mult(CS, ES)*queue\_mult(QM)*city\_mult(CS) \tag{6}$$

3.2.5. Mean Time Between Incidents

The Mean Time Between Incidents (MTBI), also stylized as Mean Time Between Failure (MTBF), represents the average duration between incidents, such as part repairs, issues with Air Traffic Control, and UAV accidents. The higher the time between failure, the safer and more reliable the system is. This metric is standard within the aviation industry and is important to assess the potential consequences in terms of cost and human life as well as provide indication of when replacement, upgrades, or maintenance is due.

MTBI is derived from using referenced average durations between incidents for different engine types (e.g., gas, electric, hydrogen, hybrid) as a baseline. The baseline number is adjusted according to the multipliers, or quantitative representations of the effect of decisions, as defined in Table 7. For example, higher cruising speeds, which correspond to more incidents, would incur a multiplier that would result in a lower MTBI.

3.2.5.1. Metric Calculation: Mean Time between Incidents

$$MTBI = mtbi\_engine(ES)*queue\_mult(QM)*pass\_mult(MNP)*city\_mult(CS)*speed\_mult(AS) \tag{7}$$

3.2.6. Passenger Comfort

Passenger Comfort reflects how the average passengers enjoys utilizing the Airport Shuttle System. As more people are willing to travel by UAM, it is critical to help ensure riders have consistently smooth and comfortable journeys. This is an important measure to attract more passengers. Variables can be found in Table 9 and Table 10.

Passenger experience attributes that were measured included: Aesthetics, Ride Experience, and Embarkment Experience. Of these attributes, the following features were assessed: Interior/Exterior Detail, Smooth Ride, Shelter, Audio/Video Content, Accessibility, Booking Ease, Noise, and Boarding Ease. The following metric used a 3-point Likert scale for evaluation as shown in Table 8.

These values were assigned to by the associated features considered for each decision in Table 9. The ratings were combined and evenly weighted to calculate a meaningful metric against key architecture enumerations.

$$A = a\_eid(CS)*w \tag{8}$$

Table 7
Metric 3 (Mean Time Between Incidents) Variables.

Identifier	Long Name	Description
mtbi_engine	Engine Mean Time Between Incidents	The base average time between incidents associated with the energy source.
queue_mult	Queue Multiplier	The quantitative effect of queue type on MTBI.
pass_mult	Passenger Multiplier	The quantitative effect of maximum number of passengers on MTBI.
city_mult	City Multiplier	The quantitative effect of city selection on MTBI.
speed_mult	Speed Multiplier	The quantitative effect of aircraft speed on MTBI.

Table 8
Three-point likert scale.

Scale	Feature is:
1	Not important
2	Fairly important
3	Very important

Table 9
Passenger experience factors considered.

Passenger Experience Attribute	Passenger Experience Feature	Identifier	Dependent Decision(s)	Associated Factors Considered
Aesthetics	Exterior/Interior Details	a_eid(CS)	City Selection	Median Household Income
Ride Experience	Smooth Ride	r_smooth(CS)	City Selection	Average Wind Speeds
		r_smooth(AS)	Aircraft Speed	Turbulence
		r_smooth(ES)	Energy Source	Vibrations
		r_smooth (MNP)	Max Number of Passengers	Mitigation of Longitudinal and Latitude Accelerations
	Audio/Video Content	r_av(CS)	City Selection	Mobile Friendly City Rating
	Accessibility	r_acc(CS)	City Selection	Reduced Mobility Demographic
	Noise	r_noise(ES)	Energy Source	Engine Noise
Embarkment Experience	Shelter	e_shlelter(CS)	City Selection	Average Rainfall
	Booking Ease	e_book(CI)	Consumer Interface	Immediacy
	Boarding Ease	e_board(QM)	Queue Method	Convenience, Wait Time

$$RE = [r\_smooth(CS) + r\_smooth(AS) + r\_smooth(ES) + r\_smooth(MNP)]*w + (r\_av(CS)*w) + (r\_acc(CS)*w) + (r\_noise(ES)*w) \tag{9}$$

$$EE = e\_shelter*w + e\_book*w + e\_board*w \tag{10}$$

$$PassengerComfort = A + RE + EE \tag{11}$$

3.2.7. *Energy Usage Rate*

The Energy Usage Rate represents the rate at which the UAV consumes its fuel source in miles per gallon, or gallon equivalent. This metric evaluates the performance efficiency of the system's critical asset. This metric is projected to have long lasting implications on aircraft design constraints, compliance with emission and noise regulations, and general user acceptance.

The UAV energy source will have a significant and direct impact on this metric because different energy sources, which have different degrees of fuel economy, serve as a baseline for the approximate fuel economy. The metric includes five variables shown in Table 11.

3.2.7.1. Calculate Fuel Economy Percentage Change (FEPC). The baseline for fuel efficiency numbers were based on gasoline-based reference helicopters that had similar seat capacities to the options for the architecture decision of maximum number of passengers. Reference aircrafts included derived mpg associated with the approximate top cruising speed. For example, the reference aircraft

Table 10
Metric 4 (Passenger Comfort) Variables.

Identifier	Long Name	Description
A	Aesthetics Score	The sum score for aesthetics
RE	Ride Experience Score	The sum score for ride experience
EE	Embarkment Experience Score	The sum score for embarkment experience
w	Feature Weight	The weight associated with each feature

Table 11
Metric 5 (Energy Usage Rate) Variables.

Identifier	Long Name	Description
speed(AC)	Aircraft Speed	The cruising speed of the UAV.
ref_aircraft(MNP)	Reference Aircraft	The average speed specifications of the reference aircrafts.
fuel_econ(MNP)	Fuel Economy	The base miles per gallon, or equivalent, of an aircraft.
percent_change(AS)	Percentage Change	The percentage change in fuel economy at different speeds.
energy_coef	Energy Coefficient	The percentage (represented as a coefficient) of energy used relative to a gasoline engine.

Table 12
Metric 6 (Annual Profit) Variables.

Identifier	Long Name	Description
pspd	Passengers Shuttled per Day	The total number of passengers shuttled per day via the UAM System. This is an argument taken from Metric 1.
ci_annual(CS,CI)	Annual Consumer Interface Cost	The annual cost to develop and implement the consumer interface passengers will use to request rides.
energy_annual	Annual Energy Cost	The annual cost of maintaining a fleet of drones.
ci_imult(CI)	Consumer Interface Income Multiplier	The quantitative representation of the perceived financial gain for consumer interface options.
city_imult(CS)	City Income Multiplier	The quantitative representation of the perceived financial gain for city selection options.
speed_imult(AS)	Speed Income Multiplier	The quantitative representation of the perceived financial gain for aircraft speed options.
passenger_size (MNP)	Passenger Size	The number of passengers an UAV can carry.
base_income	Base Income	The base fee charged to riders for a trip taken.

that can carry up to 2 people have a top cruising speed of 100 mph, 3 to 4 people have 150 mph, and 5 people has 180 mph. For architectures that selected speeds that are either lower or higher than the specified top speed, a percentage change was incurred. The percent change was calculated by taking the average of changing fuel economies for gas-fueled vehicles at different speeds. It is assumed that flying at higher speed will cause a decreased fuel efficiency.

$$\begin{gathered} if \quad speed(AC) \neq ref\_aircraft(MNP), \\ FEPC = fuel\_econ(MNP)*percent\_change(AS) + fuel\_econ(MNP); \\ otherwise, \\ FEPC = fuel\_econ(MNP), \end{gathered} \tag{12}$$

3.2.7.2. Metric Result: Calculate Energy Usage Rate. The metric is determined by the product of Fuel Economy Percentage Change and the energy coefficient. The energy coefficient was calculated by identifying the relative energy efficiency of each alternative energy source to a traditional gasoline combustion engine. For example, if a hybrid equivalent source uses 50% of the amount of energy of a gasoline vehicle, it has an energy coefficient of 2.

$$EUR = FEPC*energy\_coef(ES) \tag{13}$$

3.2.8. *Annual Profit*

The Annual Profit is the amount of money the company developing the UAM system would make in a year's time. This metric is used to assess which architectures are financially viable and how much they are expected to make or lose. Tracking the net income also provides an indication on which enumerations are most likely able to sustainably expand operations and supporting infrastructure.

The annual profit approximated the amount of money made from ride services with the cost of materials and other deductions subtracted. Variables and constants are defined in Table 12.

3.2.8.1. Calculate Annual Costs per Trip (AC). Annual costs per trip included the maintenance services required to ensure continued airworthiness as well as the development and implementation of consumer interfaces (e.g., smartphone app, website, ticket stations). The annual energy costs (energy_annual) are calculated as a function of the quantity of drones, average trip distance, drone type, and city selection.

$$AC = ci\_annual(CS, CI) + energy\_annual \tag{15}$$

3.2.8.2. Calculate Ride Profit (RP). Profit from ridership was derived by subtracting the expenses per ride from the total revenue per ride, where revenue was calculated as the product of passengers shuttled per day, the base fee for trips, and income multipliers for decisions. Income multipliers are quantitative and relative representations of the perceived financial gain for decision options. The expenses accounted for the associated flying costs, which varied based on the efficiency of the aircraft design.

$$ride\_income = pspd*base\_income*ci\_imult(CI)*city\_imult(CS)*speed\_imult(AS) \tag{16}$$

$$cost = \left(\frac{pspd}{passengers(MNP)}\right)*energy\_factor(CS)*energy\_mult(CS, ES) \tag{17}$$

$$RP = ride\_income - cost \tag{18}$$

3.2.8.3. Calculate Annual Profit (AP)

$$AP = RP - AC \tag{19}$$

Table 13
Metric 7 (Upfront Costs) Variables.

Identifier	Long Name	Description
ci_fixed(CS,CI)	Consumer Interface Cost	The cost required to develop and build the consumer interface (e.g., app, website, ticket station).
queue_fixed(QM)	Queue Fixed Multiplier	The quantitate effect of the queue method on infrastructure costs.
city_vertiports(CS)	City Vertiport Cost	The cost required to develop and build vertiports
drone_price(ES)	Drone Price	The costs required to acquire a drone.
pass_fixed(MNP)	Passengers Fixed Multiplier	The quantitate effect of the number of passengers on drone fleet cost.
speed_fixed(AS)	Speed Fixed Multiplier	The quantitate effect of the aircraft speed on drone fleet cost.
fleet_size(CS)	Fleet Size	The number of UAVs in the UAM System.
integration_mult	Integration Multiplier	The quantitate effect of UAM integration.
rdcost	Research & Development Cost	The costs associated with the research and development of the UAM system's services.

Table 14
Study Areas.

	Atlanta, Georgia (ATL)	Dallas, Texas (DFW)	Los Angeles, California (LAX)
Number of Regions	11	13	8
Unreached Regions	10	12	7
Number of Vertiports	10	12	7
Fleet Size	100	120	70
Area Served	8,376 sq. mi	9,286 sq. mi	4,300 sq. mi
Average Distance between Start/Destination Points	30 mi	23.75 mi	12.5 mi

3.2.9. *Upfront Costs*

The upfront costs metric evaluates the expenses incurred during the process of creating the UAM system. Calculating these startup costs are necessary to request funding, attract investors, and estimate expected profit. The main expenses include the fixed cost for infrastructure (e.g., helipads, consumer interface) and the fixed cost for acquiring the drone fleet. While this metric provides an indication of the magnitude of cash flow necessary, additional funds should be set aside for overlooked or unexpected expenses. Variables are defined in Table 13.

3.2.9.1. Calculate Infrastructure Cost (IC). The total infrastructure cost is calculated by approximating the expenses required to build the consumer interface that passengers need to request rides. The cost varies based on the city selected as well as the type of interface. The queue method multiplier adjusts the cost of developing the queueing system since some algorithms are more complex and resource intensive to implement. The cost for building the vertiports are added, which depends on the geographical uniqueness of the city selected.

$$IC = ci\_fixed(CS, CI)^{*}queue\_fixed(QM) + city\_vertiport(CS) \tag{20}$$

3.2.9.2. Calculate Drone Fleet Cost (DFC). The expenses incurred from acquiring a drone fleet is calculated by taking the product of the cost of an individual drone (UAV), the fleet size, and adjustment multipliers. The UAV cost depends on the energy source as engine types vary in production costs. The fleet size is dictated by the city selected since some airports will require different numbers of regions to be serviced. The multipliers consider the added cost of acquiring aircrafts with larger passenger loads and higher speeds.

$$DFC = drone\_price(ES)^{*}fleet\_size(CS)^{*}pass\_fixed(MNP)^{*}speed\_fixed(AS) \tag{21}$$

3.2.9.3. Calculate Upfront Costs (UF). The metric is determined by the summation of the infrastructure and fleet costs. However, this is adjusted by the integration multiplier. Additional research and development costs, which comprise of activities required to innovate and introduce the new service, are also considered.

$$UF = (IC + DFC)^{*}integration\_mult + rd\_cost \tag{22}$$

3.3. *Study Areas*

The initial cities that the UAM system may operate in were chosen because they are ranked as the top three busiest airports by passenger traffic in the United States (Federal Aviation Administration, 2018). These comprised of Hartsfield-Jackson Atlanta International Airport (ATL), Dallas/Fort Worth International Airport (DFW), and Los Angeles International Airport (LAX). Each airport was assessed based on its geographical data to make realistic assumptions for the model (Table 14). The number of vertiports and fleet size varies for each airport, since the areas served account for different numbers of counties and population sizes. For example, the Dallas-Fort Worth-Arlington Metropolitan Area (DFW Metroplex) encompasses thirteen north Texas Counties while the Greater Los Angeles region services eight regions, which account for less than half of DFW's square mileage (Ballinger, n.d.). As a result, the number of vertiports to include in the UAM system were calculated based on county boundaries.

Table 15
Quantitative Effects Summary for all Metrics.

		Metrics									
Decision	Options	Passengers Shuttled per Day	*Integration Readiness Level*		*MTBI*	*Passenger Comfort Index*	*Energy Usage Rate*		*Annual Profit*		*Upfront Costs*
(D_1) Consumer Interface	Smartphone App	+00:15	+0.10[1]		–	3	–		$28,000	1	$140,000
	Website	+00:05	−0.10[2]		–	2	–		$30,000	1.05	$81,000
	Ticket Station	+00:25	–		–	1	–		$15,000*21[1]	1.2	$200,000
									$15000*25[2]	1.2	
									$15000*15[3]	1.2	
(D_2) Queue	FIFO	–	–		+0.10	2,1	–		–		1
	Reservation	–	–		–	1,3	–		–		1.05
	Ride Hailing	–	−0.15		−0.10	3,2	–		–		1.2
(D_3) Maximum Passengers	1 Passenger	1	+0.05[1]	−0.05[3]	−0.05	3	12.5		–		1
	2 Passenger	1	+0.10[1]		−0.05	3	12.5		–		1.4
			+0.05[2]								
			−0.10[3]								
	3 Passenger	0.8	−0.05[1]		−0.05	2	11.4		–		1.8
			+0.05[2]								
			+0.05[3]								
	4 Passenger	0.7	−0.10[1]	+0.10[3]	−0.05	1	11.4		–		2.2
	5 Passenger	0.6	−0.10[1]	+0.10[3]	−0.05	1	5.5		–		2.6
(D_4) UAV Energy Source	Electricity	+00:30	+0.05[2]	+0.15[3]	100 k	3,3	10		30*0.045[1]		$278,000 +$5,000
									23.75*0.045[2]		
									12.5*0.045[3]		
	Hydrogen Fuel	+00:05	−0.25[1,2]		150 k	2,2	2		30*0.21[1]		$292,500 +$5,000
									23.75*0.21[2]		
									12.5*0.21[3]		
	Gasoline	+00:04	+0.10[2]		375 k	1,1	1		30*0.15[1]		$167,800 +$5,000
									23.75*0.15[2]		
									12.5*0.15[3]		
	Gas-Electric Hybrid	+15	–		250 k	2,2	1.45		0.06		$145,000 +$5,000
(D_5) City Selections	Atlanta	30	–		+0.04	2,2,3,2,3	–		1		$1,00,000*10
	Los Angeles	23.75	+0.2		–	1,1,1,1,2	–		1.05		$1,00,000*12
	Dallas	12.5	−0.1		−0.04	3,3,2,3,1	–		1		$1,00,000*7
(D_6) Speed	100 mph	100	–		–	3	+0.125		1		1
	150 mph	150	–		0.595	2	−0.12	+0.14	1.2		1.3
	180 mph	180	–		0.410	1	−0.14	1.4	1.6		

[1] Denotes Quantitative Effect used if ATL selected as city.
[2] Denotes Quantitative Effect used if DFW selected as city.
[3] Denotes Quantitative Effect used if LAX selected as city.

Table 16
Reference aircraft data.

Aircraft	Engine Type	Miles Until Refuel
Uber Elevate	Electric	60
ZeroAvia	Hydrogen Fuel	500
XTI Aircraft	Gasoline	1000
Magnus Aircraft/Siemens eFusion	Gasoline-Electric Hybrid	638

Table 17
Integration city data.

Criteria	ATL	DFW	LAX	
Web access	87.5%	82.5%	87.6%	−10% for DFW
Smartphone friendliness score	82.8	40.6	41.3	+10% for ATL

Counties that already had at least one robust public transportation system (e.g., metros, trains, bus systems) in place were excluded in the final count of "Unreached Regions." Specifically, ATL has the Metropolitan Atlanta Rapid Transit Authority (MARTA), DFW has the Dallas Area Rapid Transit (DART), and LAX has the LA Metro Line. Each unreached region was allocated one vertiport and each vertiport is assumed to house ten aircrafts at a time. The average trip distance also varies by city selection. By analyzing the area served by the airport and its relative placement, the distance between the start and end points of a trip were calculated.

3.4. Quantitative Effects

At times, the model was informed by information that could not always be directly quantifiable or the data required was not available. In either case, quantitative proxies were used to characterize these aspects when evaluating the architectures. Table 15 demonstrates how architectural decision options are quantified against the seven metrics. Rationale for all proxies are described in detail for each metric.

3.4.1. Passengers Shuttled per Day

When forecasting ridership, the consumer interface was used to determine a given passenger's wait time since different consumer interfaces are associated with faster and slower processing times depending on the degree of convenience and ease of use. This can be correlated to the UAM system's modernization level. To evaluate low modernization interfaces, New York City's transit system was used as the baseline, where passengers are required to buy metro cards from card-dispensing machines and refill their fare cards week after week or month after month. As a result, riders endured frustrating waits in long lines at card-dispensing machines in subway stations which further elongated commute times. This is analogous to the ticket station option, which incurs the longest average wait time for passengers to request rides at 25 min. It is assumed that wait times will peak in batches before and after scheduled departure and arrival flights.

For medium modernization systems, scheduling via website that operates as an online ticket sales model was used as the baseline. This system allows riders to make reservations for a given time, prepay for rides, and reduces no-shows due to the financial commitment of the booking. However, this process does not offer the immediacy of on-demand rides and either excludes potential riders who do not have access to a personal computer or internet network or lengthens wait times for riders who request rides impromptu. As a result, the website option incurs an average wait duration of 15 min to account for passengers that make reservations "on the spot."

High modernization systems can be characterized by smartphone apps since they provide the highest level of ease for the rider. It enables the user to have flexibility of their dynamic schedule and offers immediate ride service in a cashless manner. Therefore, the smartphone option correlates to the shortest wait time of 5 min.

To approximate the average number of riders per trip, the average household size for each of the three cities was taken. The model assumes that as the vehicle's carrying capacity increases, more seats are left empty on average.

Specifications for current aircrafts were used to approximate the miles until refuel as shown in Table 16 (ICAO Secretariat, 2019). For example, a gas-engine aircraft will require refueling approximately every 1000 miles. If each passenger trip is 50 miles, it can travel up to approximately 20 trips before requiring maintenance. The time to refuel to full capacity also depends on the engine type.

The selection of aircraft speed will dictate flight duration and ultimately how many trips can be taken per day. Each type of aircraft (e.g., electric) can either already fly at these speeds or are projected to fly these speeds in the near future. However, lower speeds may be necessary for flying in regulated areas or to provide passengers with safety comfort.

3.4.2. Integration Readiness Level

The calculation of integration readiness level relies heavily where the UAM system is deployed (i.e., city selection) and how easily the city can integrate other decision factors (e.g., customer interface). As shown in Table 17, the city of Dallas has 82.5% of residents with web access, whereas Atlanta and Los Angeles have 87.5% and 87.6% of residents with web access, respectively. Due to the relative lack of residents with web access in Dallas, the integration readiness level reduces by 10% if the architecture uses a website as the

Table 18
Flight hours reference data.

Energy Source	Flight Hours
Electric	2500
Hydrogen fuel cell	375
Gas	937.5
Hybrid	625

Table 19
Noise level data.

Engine Type	Noise Level (dB)
Electricity	55
Hydrogen Fuel	65.5
Gasoline	80.5
Gas Electric Hybrid	70

customer interface and the city of Dallas as the city selection. In a similar vein, there is a 10% increases to the integration readiness level if the architecture uses a smartphone app as the customer interface and the city of Atlanta as the city selection due Atlanta's high smartphone-friendliness score relative to Dallas and Los Angeles.

The maximum number passengers compared to the average number of residents per household to increases the integration readiness level of Los Angeles (2.82 per household) for aircraft with 4 or 5 passengers and increases the integration readiness level of Atlanta (2.22 per household) for aircraft with 1 or 2 passengers. The energy source increases the integration readiness level for architectures with electric and hydrogen fuel cell engines in cities that have relatively high numbers of electric and hydrogen fuel cell cars. The city selection also evaluates the number of helipads, airspace classification, and number of daily flights to increase the integration readiness level for cities with many existing helipads, accessible airspace, and high volume of air traffic.

There are other effects on the integration readiness level which are city-agnostic, such as queue method. This analysis assumes that all passengers are familiar with FIFO and reservation queue models, but provides a −15% punishment for ride hailing because only 36% of urban residents of Uber/Lyft, so the ride hailing may be unfamiliar to a large portion of city residents.

3.4.3. Mean Time Between Incidents (or Mean Time Between Failures)

The most significant factor for calculating the mean between incidents (or mean time between failure) is the energy source. Using existing UAVs and car engines as a reference, the following quantity of flight hours in Table 18 is used for the calculation:

This engine failure rate factors into a generic UAV reliability calculation which assumes other components of the UAV (e.g., sensors) will fail every 50,000 flight hours. The calculation is:

$$\frac{1}{\frac{1}{EngineFlightHours} + \frac{1}{50{,}000} + \frac{1}{50{,}000} + \frac{1}{50{,}000}} \tag{23}$$

Finally, these failure rates are affected by multipliers that account for other factors which affect the mean time between incidents, including maximum number of passengers, local air traffic, and flight speed.

3.4.4. Passenger Comfort Index

Due to the subjective nature of passenger comfort, quantitative proxies were taken for each architecture decision to evaluate overall ride experience. For example, the consumer interface and queue method both correlate to the passenger's embarkment experience and therefore to the passenger comfort.

The maximum number of passengers is one of the factors used to assess the smoothness of the ride. A flight that transports more passengers is more vulnerable to a bumpier ride. Passengers will also need to be seated close to the center of gravity of the aircraft to mitigate longitudinal and lateral accelerations (i.e., turbulence) that may cause motion sickness.

In addition, the UAV energy source is used to assess the ride experience. For example, electric motors provide smooth and immediate acceleration whereas gas vehicles use internal combustion engines which rely on combustion and moving mechanical parts, and therefore may attribute to an uneven ride. Additionally, the noise level (dB) for each engine type was gathered from available specifications and consolidated in Table 19. Lower noise levels correlate to a better passenger comfort level.

City selection also contributes to various passenger experience, as this decision affects ride smoothness, aesthetics, shelter, audio/video content, and accessibility. The average wind speeds for each city were accounted for determining a smooth ride (Osborn, 2020). The median household income for each city was gathered to gauge the importance of interior and exterior aesthetics of the aircraft (Deloitte et al., n.d.). The average rain fall, in inches, determines the necessity of building more robust shelters for riders waiting to board the vehicles (Sperling, 2020). Each city is associated with a mobile friendly city rating, which is used to determine the importance of having audio/video enabled technologies for riders in route to their destination (Ramirez and Todd, 2017). The reduced mobility demographic was analyzed to determine the level of catering needed for those with accessibility needs (United Way of Denton County, Inc., 2017). Some of the data for these factors is shown in Table 20.

Table 20
City data.

Proxies	ATL	DFW	LAX
Median household income	$65,345	$52,210	$68,093
Average wind speeds (mph)	9.1	10.7	6.9
Average rain (in)	52	39	16
Mobile friendly city rating	1	26	25
Reduced Mobility	8.8%	5%	10%

Table 21
Aircraft reference data.

Aircraft	Passenger Capacity	Range	Tank Capacity	mpg	Top Speed
Robinson R22	2	240	19.2	12.5	112
Robinson R44	4	350	30.6	11.4	149
Robinson R66	5	400	73.6	5.4	161

3.4.5. *Energy Usage Rate*

Currently, there are a limited number of passenger VTOL vehicles under development, which complicates the energy usage rate calculation. As a result of lack of data available on real-world passenger drones and the significant improvements expected in the UAM aircraft technology and alternative fuel technologies, an analogous comparison was chosen: helicopters. The model uses helicopter fuel efficiencies as an input to generate the equations for calculating energy efficiencies for the architecture decisions, as shown in Table 21. Fuel efficiencies were calculated by using the aircraft range divided by the main gas tank capacity.

The energy usage rate for each of the model's energy sources is calculated by identifying the energy efficiency of each alternative energy source compared to a traditional gasoline internal combustion engine. For gas-electric hybrids, the easiest method of derivation was to compare passenger cars to their hybrid equivalent (e.g., Honda Civic, Toyota Camry). Hydrogen fuel cells will generally use 50% the amount of energy that a gasoline vehicle uses (Eichman & Flores-Espino, 2016), which doubles the fuel efficiency. The coefficient for electricity was taken from the Uber Elevate study (Uber Elevate, 2016).

Lastly, the derived MPG is affected by the approximate top speed of the aircrafts. The model assumes that flying at higher speeds will cause a decrease in fuel efficiency (Barth, 2009).

3.4.6. *Annual Profit*

Annual profit is calculated by determining the annual revenue, then subtracting the annual cost to run the system. Revenue is calculating how many passengers are shuttled per year, then multiplying the number of annual passengers by a $50 per passenger. The model uses $50 as its base ticket price because it falls near the median of the assumed price of relevant publications on financially viable UAM systems (Hasan, 2018). There are various small multipliers (i.e., 1–5%) which factor into this calculation, such as each city's income.

The annual cost is calculated by determining the annual energy cost, which is calculated by taking cost of fuel per trip and multiplying by average trip length, then multiplying this value by the number of annual trips. Next, the annual maintenance cost is determined by summing a fixed maintenance cost (which is proportional to the cost of purchasing the UAV fleet) and the variable maintenance cost, which is a function of the mean time between incidents. Then, the annual infrastructure cost, which is a combination of operating the customer interface, insurance costs, technology upgrades, and vertiport upkeep, is calculated. Finally, each of these annual costs are summed to determine the total annual cost.

The annual profit is determined by subtracting the annual cost from the annual revenue. Both the annual revenue and annual cost are stored for analysis in addition to the annual profit.

3.4.7. *Upfront Costs*

The first step in calculating the upfront cost is to determine the cost of developing the customer interface, with building ticket stations being significantly more expensive than developing a smartphone app or website. Next, the model assigns $1,000,000 as the cost to build each vertiport with different quantities of vertiports required to serve each city. There is a small multiplier which reflects that it will be easier to roll out a customer interface in cities that are already comfortable with that interface type and build vertiports in cities that have existing helipad infrastructure.

Next, the model calculates the cost of purchasing the drone fleet. The baseline cost of the drone is estimated based on both the actual cost of purchasing a drone with each energy source (e.g., electric) while also considering the relative cost of cars that use each energy source (e.g., electric cars) to account for the fact that the differences in prices of these UAV energy technologies are likely to be closer to the relative costs of their automotive counterparts by the time one initiates this project. There are multipliers that reflect the fact that larger drones (i.e., more passengers) are more expensive than smaller drones and that faster drones are more expensive than slower drones. Once the cost to purchase each drone is determined, the model multiplies the necessary drone fleet size for each architecture.

Finally, the upfront cost is calculated by summing the cost to develop the customer interface, the cost to build UAM infrastructure,

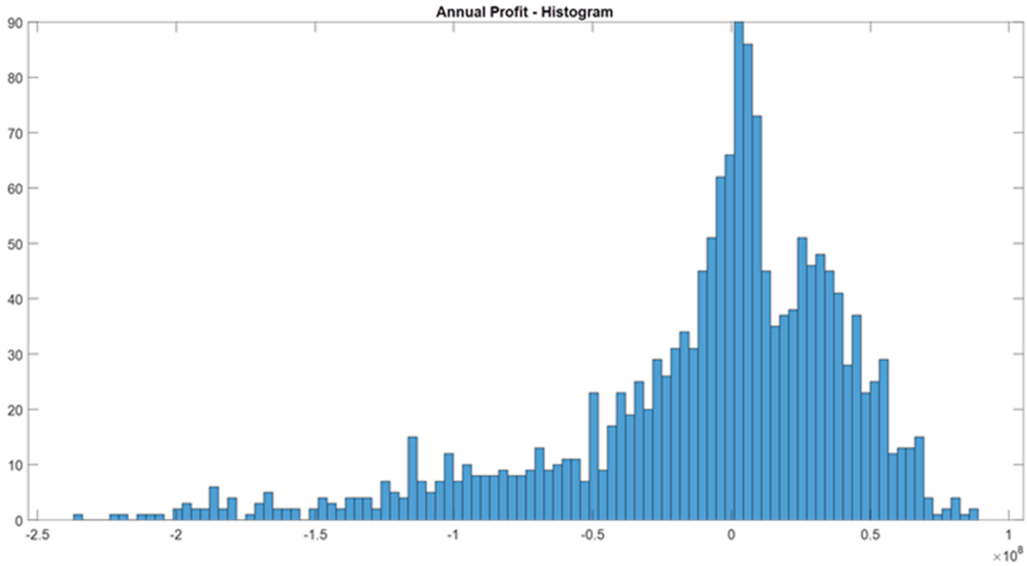

Fig. 3. Annual profit histogram.

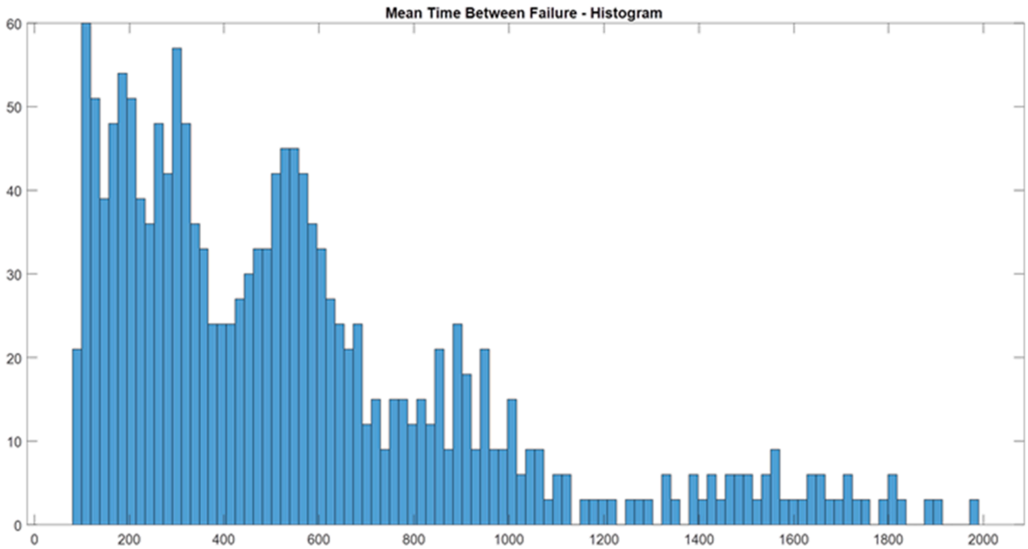

Fig. 4. Mean Time Between Failure – Histogram.

and the cost to purchase the drone fleet.

4. Model Results

4.1. Major Findings

Based on the established metrics discussed above, numerous tradespace analyses are conducted to examine the correlation and interrelationships between decision variables and performance metrics. Among the seven metrics, this analysis focuses on the interrelationships between Annual Profit, Mean Time Between Incident (MTBI), Upfront Cost, and Passengers Shuttled Per Day. Specifically, the model examines the range of variation amongst architectures, notable tradespaces pertinent to primary stakeholders, and dominant features amongst these tradespaces. This study concludes by examining the sensitivity to and connectivity of metrics used in this analysis.

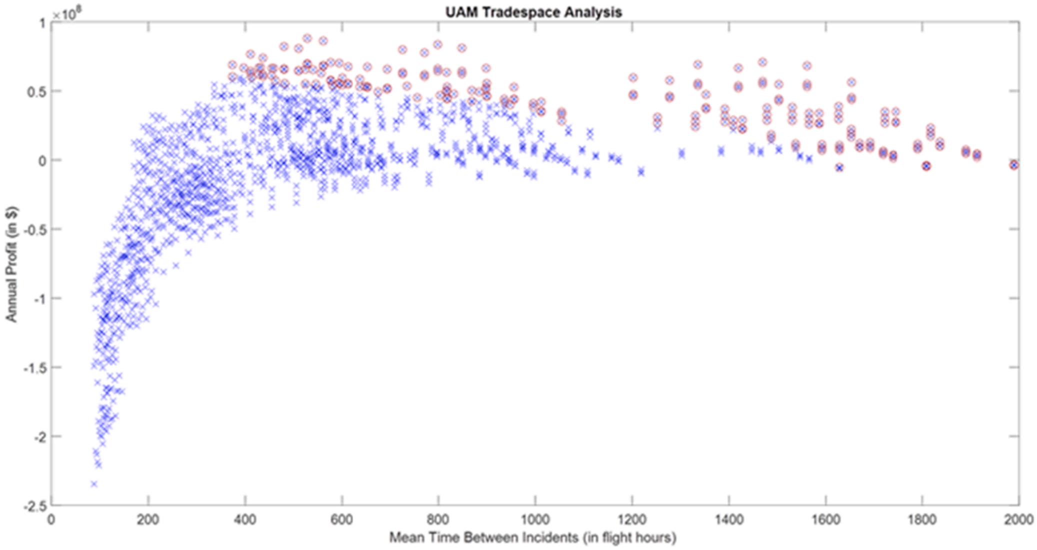

Fig. 5. Tradespace – MTBI vs. Annual Profit.

Table 22
Dominant features of MTBF vs. Annual Profit on True Pareto Front.

	Customer Interface	Queue Type	Maximum Passengers	Energy Source	City	UAV Speed
Option 1	**0.92**	**1.00**	0.23	**1.00**	0.15	0.69
Option 2	0	0	0.23	0	0.15	0.15
Option 3	0.08	0	0.08	0	0.69	0.15
Option 4	N/A	N/A	0.23	0	N/A	N/A
Option 5	N/A	N/A	0.23	N/A	N/A	N/A

Note: Option 1, Option 2, and so on, refers to the potential options for each of the decisions in the columns of the table above. For example, the Customer Interface decision has Smartphone App as Option 1, Website as Option 2, and Ticket Station as Option 3. Both Option 4 and Option 5 are excluded from the table because there are only three options for the Customer Interface decision.

4.1.1. *Annual Profit*

Fig. 3 shows the distribution of annual profit for architectures in this trade space, which broadly range from roughly negative $240 M to positive $90 M. Interestingly, the most common outcome is a profit of around $0. This speaks to the complications around commercial viability of such a system and specifically that a business in this sector comes with considerable risk. Although this data implies a difficult market today, it is believed that eminent technological enhancements to design elements considered in this analysis will allow for a higher likelihood of profitability. Namely, breakthroughs in energy efficiency, traffic management, and perhaps new types of UAVs not even envisioned, will allow for greater throughput at lower cost with an increased factor of safety.

4.1.2. *Mean Time Between Failure*

When considering the reliability of the system, Fig. 4 indicates that most architectures result in an MTBI of approximately 100 h. Operating at 19 h a day, this roughly translates to an incident every 5 days which is notably high. This speaks to an overwhelming need to regulate implementations of such systems. Regulatory Bodies will be interested in shifting these trends towards the right of this graph and more importantly, analyzing the architectures that contribute to this spike to better understand how to enforce safe operating conditions. This information also has implications on public opinion in that it will likely promote a narrative that UAM systems are unsafe. As discussed in the literature review, one of the biggest constraints in adopting this technology is the perception of safety. This has important implications for the design and success of the system since people will not use the system if there is an incident this frequently.

4.1.3. *Tradespace: Mean Time Between Incidents vs. Annual Profit*

When evaluating the reliability against the profitability, the analysis revealed that the more incidents that occur (less time between incidents), the less profitable a system will be. Regulatory bodies will of course want to ensure that operations are handled safely. This proves though that in addition to regulatory pressures, private industry will be financially motivated to ensure that the services provided are without incident. As can be seen in Fig. 5, a large portion of the architectures both have low MBTI and are not profitable. Adjusting for a few outliers, this analysis suggests that a system should target a minimum 1200 h between incidents to be profitable.

On the true Pareto front (Table 22), which represents architectures that are non-dominated (i.e., no other architecture has both

Table 23
Dominant features of MTBF vs. Annual Profit on Fuzzy Pareto Front.

	Customer Interface	Queue Type	Maximum Passengers	Energy Source	City	UAV Speed
Option 1	0.53	**0.71**	0.14	**0.92**	0.14	0.68
Option 2	0.22	0.24	0.14	0	0.18	0.18
Option 3	0.25	0.05	0.19	0.08	0.68	0.14
Option 4	N/A	N/A	0.28	0	N/A	N/A
Option 5	N/A	N/A	0.25	N/A	N/A	N/A

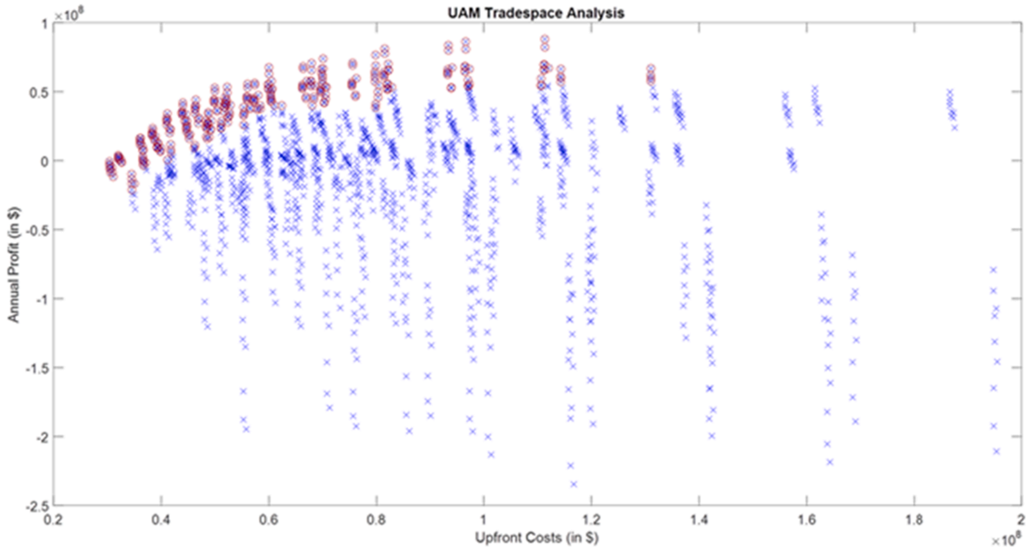

Fig. 6. Tradespace – Upfront Costs vs. Annual Profit.

Table 24
Dominant features of Upfront Cost vs. Annual Profit on True Pareto Front.

	Customer Interface	Queue Type	Maximum Passengers	Energy Source	City	UAV Speed
Option 1	**0.72**	**1.00**	0.08	0.24	0	0.64
Option 2	0	0	0.16	0	0	0.2
Option 3	0.28	0	0.24	0.52	**1.00**	0.16
Option 4	N/A	N/A	0.32	0.24	N/A	N/A
Option 5	N/A	N/A	0.2	N/A	N/A	N/A

higher MTBF and higher annual profit), the model finds that utilizing a FIFO Queue and utilizing an Electric Energy Source are present on 100% of these architectures. This indicates that these features are essential to architectures which are both safe and profitable.

On the fuzzy Pareto front (Table 23), which represents architectures that are ranked in the top five of the tradespace's Pareto front, the model finds that utilizing a smartphone app is present on at least 70% of these architectures and/or the architectures on the true Pareto front. This indicates that this feature is quasi-necessary to architectures which that both safe and profitable.

4.1.4. Tradespace: Upfront Costs vs. Annual Profit

When implementing a UAM airport shuttling system, the greater the amount of money spent up front, the higher the potential annualized profit will be, but only to a point. Specifically, the upper bound of profit increases per dollar spent up to around $120 M at which point there are diminishing returns as demonstrated in Fig. 6. This makes sense as the broader the operation is upfront, the more difficult it will be to maintain. It is also worth noting though that as upfront cost increases, so does the range of profit within the trade space. This tells us that while if more is spent upfront the potential profit increases, so does the potential for loss. Therefore, for a UAM airport shuttling business (i.e., private industry) to have the potential for the highest profit point it should spend approximately $120 M up front, however it also then has the largest potential for loss.

On the true Pareto front (Table 24), which represents architectures that are non-dominated (i.e., no other architecture has both lower upfront cost and higher annual profit), the model finds that utilizing a FIFO Queue and targeting Los Angeles are present on 100% of these architectures. This indicates that these features are essential to architectures that are both inexpensive to develop and profitable while operating.

Table 25
Dominant Features of Upfront Cost vs. Annual Profit on Fuzzy Pareto Front.

	Customer Interface	Queue Type	Maximum Passengers	Energy Source	City	UAV Speed
Option 1	0.46	0.48	0.1	0.24	0	0.63
Option 2	0.24	0.37	0.13	0	0	0.22
Option 3	0.3	0.15	0.24	0.5	**1.00**	0.15
Option 4	N/A	N/A	0.29	0.25	N/A	N/A
Option 5	N/A	N/A	0.23	N/A	N/A	N/A

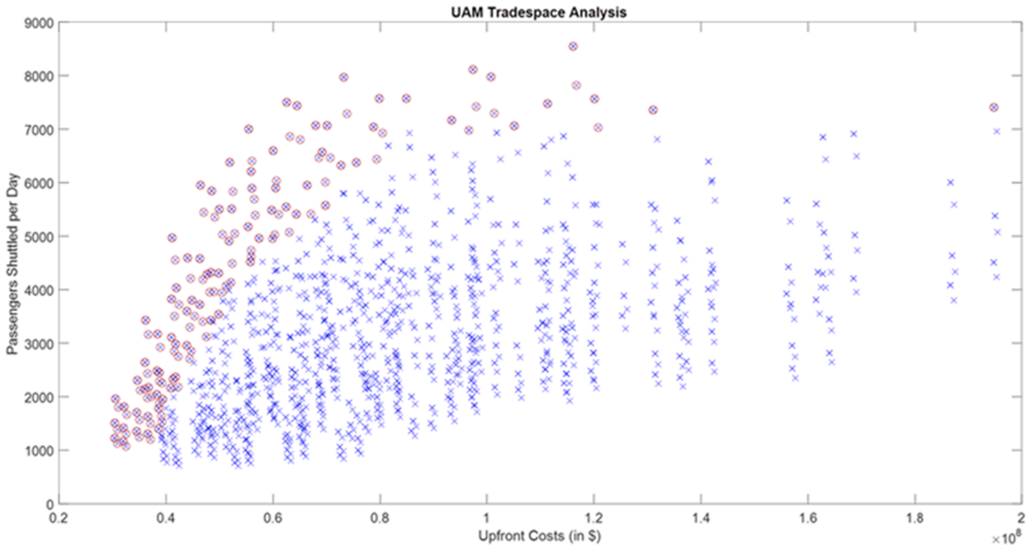

Fig. 7. Tradespace – Upfront Costs vs. Passengers Shuttled per Day.

Table 26
Dominant Features of Upfront Cost vs. Daily Passengers on True Pareto Front.

	Customer Interface	Queue Type	Maximum Passengers	Energy Source	City	UAV Speed
Option 1	**0.73**	**1.00**	0.27	0	0	0.6
Option 2	0.2	0	0.13	0.13	0	0.27
Option 3	0.07	0	0.13	0	**1.00**	0.13
Option 4	N/A	N/A	0.13	**0.87**	N/A	N/A
Option 5	N/A	N/A	0.33	N/A	N/A	N/A

On the fuzzy Pareto front (Table 25), which represents architectures ranked in the top five of the tradespace's Pareto front, the model finds that utilizing a FIFO queue and utilizing a smartphone app are present on at least 70% of these architectures and/or the architectures on the true Pareto front. This indicates that these features are quasi-necessary to architectures which are both inexpensive to develop and profitable.

4.1.5. *Tradespace: Upfront Costs vs. Passengers Shuttled per Day*

As displayed by the UAM tradespace in Fig. 7, upfront cost has a major impact on the passengers shuttled per day. This is because with a healthy amount of capital expenditure dedicated to the queuing method, customer interface, and passenger capacity, the more capable the UAM operation is at maximizing passenger throughput. However, as you exceed over approximately $120 million, the output tends to plateau and slightly decrease as passengers start to overwhelm the handling capability of the UAM system despite the additional dedicated funding towards the operation.

On the true Pareto front (Table 26), which represents architectures that are non-dominated (i.e., no other architecture has both lower upfront cost and higher passengers shuttled per day), the model finds that targeting Los Angeles is present on 100% of these architectures. This indicates that selecting Los Angeles is essential to architectures that are both inexpensive to develop and shuttle many passengers.

On the fuzzy Pareto front (Table 27), which represents architectures ranked in the top five of the tradespace's Pareto front, the model finds that utilizing a FIFO queue, utilizing a smartphone app, and utilizing a hybrid energy source are present on at least 70% of these architectures and/or the architectures on the true Pareto front. This indicates that these features are quasi-necessary to

Table 27
Dominant Features of Upfront Cost vs. Daily Passengers on Fuzzy Pareto Front.

	Customer Interface	Queue Type	Maximum Passengers	Energy Source	City	UAV Speed
Option 1	**0.73**	0.43	0.24	0	0	0.54
Option 2	0.17	0.33	0.18	0.09	0	0.28
Option 3	0.1	0.23	0.19	0.3	**1.00**	0.18
Option 4	N/A	N/A	0.19	0.61	N/A	N/A
Option 5	N/A	N/A	0.2	N/A	N/A	N/A

Table 28
Decision-to-Metric Sensitivity Analysis.

Decisions	MTBF	Integration	Passengers Shuttled	Passengers Experience	Upfront Cost	Annual Profit	Annual Revenue	Annual Cost
Customer Interface	0	0.029	827	13.6	73,238	8,091,890	13,719,478	20,958,375
Queue Type	55	0.102	171	4.1	404,699	6,218,119	4,114,418	3,833,017
Max Passengers	46	0.007	**1222**	3.0	**20,455,185**	13,109,205	**29,464,030**	16,354,825
Energy Source	**369**	0.087	185	12.8	19,663,055	**46,368,063**	4,386,281	**48,823,066**
City Selections	22	**0.237**	1,006	**46.4**	20,420,081	17,618,082	25,087,366	7,469,284
UAV Speed	286	0	408	3.1	14,137,065	17,334,346	22,098,858	38,089,739

Note: the scale of sensitivity analysis varies across metrics (in columns), but within each metric, the sensitivity score for each architecture decision (in rows) can be compared with other sensitivity scores. The highest relative sensitivity score within each metric is bolded to indicate which architecture decision each metric is most sensitive towards.

architectures which are both inexpensive to develop and profitable (see Table 28).

4.1.6. Sensitivity Analysis

The sensitivity analysis evaluates which architecture decisions (in rows) have the most impact on each metric (in columns). These results make sense as, for example, one would expect the architecture decision of which energy source to utilize would have the most impact on the mean time between failure. Additionally, the city selection is the most impactful architecture decision in determining the integration readiness level, which makes sense because each city will be very sensitive to how the UAM system integrates into their existing infrastructure and demographics. One should note that the sensitivity is only scaled for each metric (i.e., within each column), so the most impactful architecture decision is bolded for each metric to improve comprehensibility.

4.2. Major Recommendations

The analysis presented in this paper yields several meaningful recommendations for those interested in implementing an airport shuttling UAM system. These recommendations are considered through the lens of the various stakeholders and their unique needs. With capital investment and respective returns in mind, considerations of the private sector align well to the advantages of utilizing Los Angeles as a pilot city for this system. Their interests will be best served by leveraging a FIFO queuing system and a smartphone-based consumer interface. These recommendations are based on the dominant features discovered in analyzing annual profit against MTBI and upfront cost. Similarly, it was determined that the same pilot city, queuing method, and interface were dominant in analyzing impacts to the number of daily customers. A hybrid energy source was also dominant in this domain. Keeping in mind the overall traffic of using an UAM system, these attributes are recommended as advantageous to meeting the needs of the general public. Lastly, due to these being the dominant features when exploring impacts to MTBI, governing bodies should utilize the same queuing technique and check in methodology. The fuel source that best meets their needs however would be electric energy.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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