AN INTEGRATED VERTIPORT PLACEMENT MODEL CONSIDERING VEHICLE SIZING AND QUEUING.

Carl Khalife
Research Assistant
Centre for Transport Studies
Department of Civil and Environmental Engineering
Imperial College London
SW7 2BU, UK

Joseph Slim
Masters in Engineering Student
Centre for Transport Studies
Department of Civil and Environmental Engineering
Imperial College London
SW7 2BU, UK

Jose Escribano Macias, Ph.D., Corresponding Author
Research Associate
Centre for Transport Studies
Department of Civil and Environmental Engineering
Imperial College London
SW7 2BU, UK
jose.escribano-macias11@imperial.ac.uk

Panagiotis Angeloudis, Ph.D.
Reader in Transport Systems and Logistics
Centre for Transport Studies
Department of Civil and Environmental Engineering
Imperial College London
SW7 2BU, UK

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ABSTRACT
The increasing levels of congestion and infrastructure costs in cities have created a need for more intelligent transport systems. Urban Air Mobility (UAM) offers a solution by introducing intra-urban aerial transport to overcome the existing congested infrastructure. The performance of UAM systems are highly dependent on vertiport locations, vehicle sizing and infrastructure specifications. This study takes a holistic approach to UAM network optimisation by considering the inter-relatedness of these decisions. A vertiport placement model with vehicle sizing constraints is developed to determine the optimal vertiport configuration while considering eVTOL performance. The resulting configuration is used to model waiting times depending on infrastructure specifications. These waiting times are incorporated in the vertiport placement and vehicle sizing models. An iterative approach is undertaken to find the network configuration that balances the infrastructure, operational costs as well as passenger waiting times. The purpose of the study is to inform policy-making by proposing a holistic approach to UAM network design.

Keywords: vertiport placement, urban air mobility, queuing theory, vehicle sizing

INTRODUCTION

Urban Air Mobility (UAM) as a concept has been pursued by research and industry since the mid-1900s, yet only recently has technology reached the level of maturity required to make urban air travel economically feasible. By September 2018, approximately \$1 billion was invested in UAM, and over 70 electrical vertical take-off and landing (eVTOL) manufacturers were founded (*1*), highlighting the industry's potential market value.

While UAM includes varied operation types, one of its most promising aspects is On-Demand Air Mobility (ODAM), which envisions a demand-responsive operational model to serve intra- and inter-urban transportation, as well as short-haul flights that are not sustainable using traditional aviation (*2*). ODAM seeks to solve two of the main problems that are expected to shape the future of the aerospace industry: demand for increased travelling speeds and the need for reduced emissions (*3*). Its potential market size is currently valued at \$2.5 billion in the first years of operations and increase to up to \$500 billion (*1*).

ODAM is expected to operate between a network of vertiports, which have take-off, landing and charging capabilities. These can be retrofitted into existing infrastructure such as unused helipads or highway cloverleafs, to significantly reduce the initial investment cost compared to traditional modes of transport (*4*).

Recently, several initiatives have launched to further develop the field of ODAM. Uber expressed its aspiration to launch an air-taxi service in the near future through the Uber Elevate initiative (*4*). Additionally, alongside NASA, Uber Elevate organises yearly conferences and workshops to form a community centred around building solutions for UAM development (*4, 5*). NASA is also developing new air-traffic management methods that accommodate ODAM operations into the urban airspace (*6*).

(*7*) reported that achieving a return on invested capital in the ODAM market is possible even for small networks, but highlight that the cost of charging and refuelling will significantly affect the business case. At the same time, the study stresses the importance of ensuring very fast turnaround times in minimising the total operating costs. Turnaround time is governed by many factors, such as the number of pads at each vertiport, battery capacity, charging rate, length of trips as well as the dispatch strategy.

These findings suggest vertiport placement models that determine the optimal configuration of supporting infrastructure, as well as vehicle parameters, are essential in ensuring the viability of ODAM systems. Failing to do so results in network configurations which are infeasible from an operational perspective. For example, neglecting vehicle sizing constraints in the vertiport placement model might lead to configurations where the operational requirements are not satisfied. Further, neglecting the effects of the number of pads at each vertiports on waiting times, might lead to underestimating turnaround times. However, our review of current literature suggest that an integrated solution that encompass these aspects is yet to be developed (see Section 3).

To address this gap, this paper proposes an approach to designing air-taxi networks by considering the optimisation of three inter-related decisions: vertiport locations, vehicle and infrastructure specifications. Each decision is captured in a stage, with vertiport locations being determined through a hub-location problem, and infrastructure specification being obtained using Jackson open network theory. An iterative algorithm is developed that solves three stages sequentially, improving the solution through a feedback mechanism that updates problem parameters until an optimal solution is achieved.

The paper's contribution is threefold:

1. To the authors' knowledge, it is the first study to propose a methodology to design a UAM network considering the interrelationships between vehicle sizing, vertiport infrastructure and network design.
2. It models vertiport operations using open network theory, instead of relying on network simulation usually found in literature.
3. It presents a computationally efficient solution heuristic that can accommodate large problem instances. A case study based on the hypothetical design of a London UAM system, in which our algorithm shows significant improvement in all metrics compared to our benchmark.

The remainder of the paper is structured as follows. An analysis of the current state of the art is presented in the next section, followed by a description of the mathematical model and formulation. After, the case study based on the city of London is introduced and the results of our algorithms are presented and analysed. Finally, our concluding section suggests further works.

CURRENT APPROACHES IN ODAM NETWORK DESIGN

This section reviews the state-of-the-art in the field of ODAM vertiport location planning and vehicle sizing. A summary of the literature reviewed is presented in Table 1, highlighting the features unique to our methodology.

Vertiport Location

The vertiport placement problem is generally structured as a facility or hub location problem, in which the geographical position of hubs is determined to optimise a specific objective. The literature of the facility location problem is extensive (*8*), with one of the first formulations being proposed by (*9*), known as p-median problem.

Extensions to the original problem have been proposed for multiple applications (*10*). However, the p-median formulation provides an adequate framework to model vertiport placement models, as it allows the positioning of hubs to be governed by economical metrics, such as the travel time savings, weighted demand distance, and infrastructure costs.

Within this framework, (*4*) proposed an initial network configuration model applied to Los Angeles and London case studies. A clustering algorithm is used to group the demand into discrete facility candidate locations, and a facility location algorithm is developed to maximise trip coverage.

Another vertiport placement model is presented by (*11*) that assumes short-term eVTOL demand is driven by high income car users with large travel times. Consequently, the objective is to maximise the total travel time savings relative to driving, but ignores the investment costs relating to infrastructure development and costs of operations. In fact, operational constraints are not evaluated, as vertiports are given unlimited capacity to allow the optimisation not to focus too many ports in areas of large demand.

A capacitated p-median problem instance is explored by (*12*). A neighbouring searching algorithm is used to partition service region into catchment areas for each supporting facility and select the optimal placement that minimise weighted demand distance.

(*13*) presented an uncapacitated p-median formulation to solve the vertiport placement problem for airport strips, where demand is estimated using airport incoming hourly trips. Selected vertiports are then modelled as an M/M/c queue system during post-processing, to determine the potential market penetration at each port.

Operational parameters are incorporated to the vertiport placement problem by (*14*). The study proposed a two stage model for vertiport placement and operation scheduling problem, where the latter optimises the charging scheduling of vehicles to minimise total delay for all passengers. However, given that the stages are produced in sequence without feedback the algorithm will not produce optimal results, as the operations model is executed as a post-process.

Deviating from the original hub location formulation, (*15*) and (*16*) both propose a vertiport location problem using a k-means clustering approach. Without applying the hub location problem formulation, this approach is unable to consider factors relating to the operation, cost, or capacity of the infrastructure.

To date, no vertiport placement study considers vehicle sizing, charging and operational constraints. Without notion of such concepts, the resulting vertiport configuration could lead to vehicle designs with unreasonable battery masses, charging requirements, and costs.

Vehicle Sizing

This stream of research aims to determine the optimal power and battery requirements for vehicles to sustain operations, which requires uses set mission parameters as input, namely the flight time requirements and charging time requirements.

Among the most widely employed tools to design air vehicles is NASA's Design and Analysis Rotorcraft (*17*), which has already been used to design air-taxi vehicles (*18, 19*).

(*20*) proposed a cruise depletion rate parameter to encompass the energy performance into a single parameter. The approach is refined in (*21*) in order to incorporate relationships with other critical vehicle properties, such as vehicle mass. The iterative process in (*21*) assumes a power loading parameter for each mission segment to determine the battery size that achieves the specified mission requirements.

Another vehicle design tool is presented by (*22*) that compares the performance of VTOL and STOL aircraft in terms of maximum take-off weight given varying flight ranges and cruise speeds. (*23*) developed a vehicle sizing model focusing on noise emission, power/energy consumption rates, and costs in the context of UAM.

Deviating from the previous literature, (*24*) performed a weight-based optimisation with consideration of range, speed, rotor size, wing loading and battery energy density parameters. Weight is assumed to act as a proxy for the direct operational cost.

This section reveals that vehicle sizing is mainly driven by cost, which is dependent on the required levels of cruise and hover specified by the mission profile. Nevertheless, the provision of insufficient supporting infrastructure in the form of vertiports or landing areas may lead to significant loiter times, which would require a larger battery size, therefore driving up costs, while also increasing turnaround times.

However, current research does not consider the effect of loiter time on vehicle performance, vertiport placement and costs. These can be estimated using UAM network simulation, which have been developed with varying level of detail (*20, 25–27*).

While simulation-optimisation frameworks can be used to optimise network design using agent-based models, the approach will never yield an optimal solution, and an analytical approach is nevertheless required to benchmark the output of the simulation. Furthermore, the simulation speed becomes the limiting factor of the optimisation, which increases as the scope increases in size and complexity.

TABLE 1 Literature summary

Focus	Author	Approach	Objective	Features
Vertiport Location	(*4*)	C, EA	WD	Demand aggregation
	(*11*)	EA	TS	Traffic; Demand
	(*12*)	EA	WD	Vertiport capacity
	(*13*)	EA	TS	Transfer; Queue post-process
	(*14*)	C	TT	Charging; Scheduling
	(*15*)	C	D	Case Study
	(*16*)	C	D	Time Savings
Vehicle Sizing	(*18*)	-	W	Aircraft layout
	(*19*)	-	W	Aircraft layout
	(*20*)	-	W	Energy source
	(*21*)	-	C	Battery size
	(*24*)	-	W	Aircraft layout
This paper		EA	TS	Queuing; Battery size

Legend:
Approach: C - K-means clustering, EA - Exact algorithm.
Objective: C - Cost, D - Distance, TT - Travel Time, TS - Travel Savings, WD - Weighted Demand, W - Weight.

Contribution

The infrastructure limitations in vertiports (number of charging, take-off and landing pads) suggests that vehicle fleets will experience loitering during operation. The available loiter time of vehicles is determined through vehicle sizing. As such, the vertiport placement models that ignore the loitering and infrastructure requirements will result in operationally infeasible configurations. While network simulations can be used to model operations in simulation-optimisation frameworks, they lack practicality due to the large run times of existing simulations.

To solve the integrated network design and vehicle sizing problem, this paper proposes a three stage iterative approach. In the first instance, a modified p-means hub location model is used to determine the optimal geographical position of vertiports. The outputs of this stage serves as the inputs to the vehicle sizing model that calculates the vehicle battery size requirements given the operational requirements of the proposed UAM network. The final stage uses a queuing model to estimate loiter times and define the infrastructure requirements of the vertiports. A feedback loop collects the results of the infrastructure model and modifies the initial vertiport placement model. This process is repeated until the marginal cost of operating an additional pad outweighs the marginal benefit of doing so. The proposed approach allows us to model the inter-dependencies between between various UAM decisions, while also finding the configuration that optimises operational, infrastructure costs as well as service times.

METHODOLOGY

This paper proposes a holistic approach to UAM network optimisation, the objective is to determine the optimal location of vertiports given pre-defined demand intensity, as well as determining the appropriate vehicle battery size and vertiport properties that minimise overall implementation

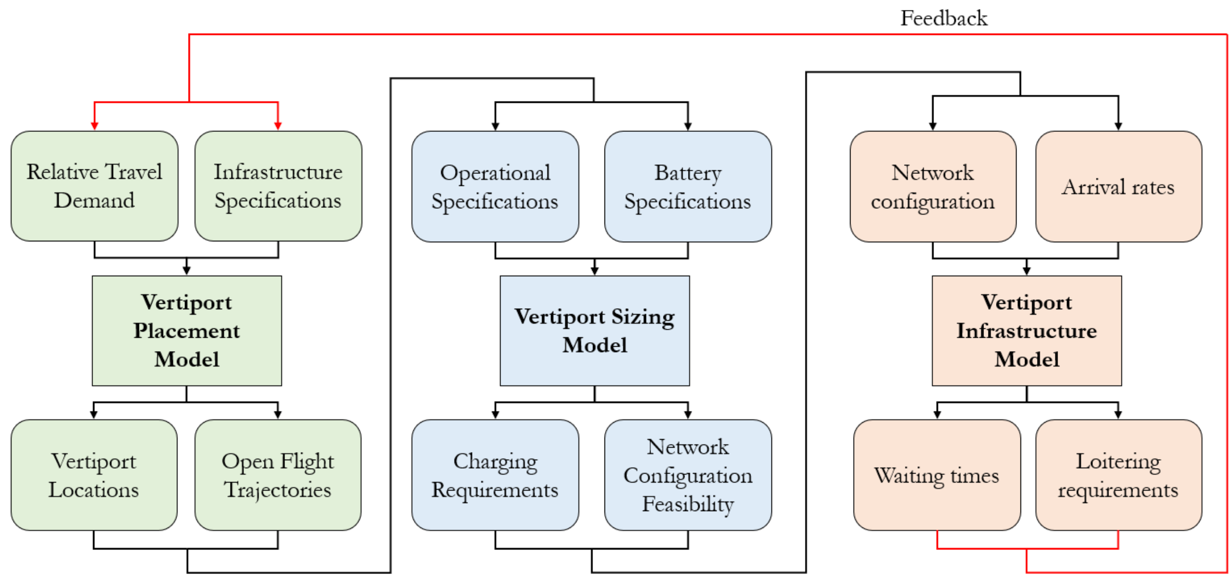

FIGURE 1 Solution method workflow. Highlighted in green are the inputs, processes and outputs of the vertiport placement model, in blue the vertiport sizing model, and in orange the infrastructure model.

costs. A three-stage algorithm is presented composed of a linear vertiport placement model, a vehicle sizing stage, and an infrastructure model.

The vertiport placement model focuses on selecting the vertiport locations that maximises travel savings to customers provided. In doing so, the proposed model ensures that selected links between the vertiports conform with the operational constraints defined by the aircraft and infrastructure properties.

The vehicle sizing stage determines the battery size that satisfies the energy requirements outlined by the placement model. Once the battery size is determined, the charging requirements are calculated based on the C-rate and discharge rates of the battery, which vary based on its mass and the specific energy of the vehicle.

Finally, the infrastructure model is applied to each vertiport to determine their service rate requirements. Utilising open network theory, the congestion at the vertiports is modelled, and the allowed loiter times based on the number of landing, charging and take-off pads throughout the network is calculated. As network theory requires arrival demand rates, these are obtained from agent-based modelling tools at the beginning of the optimisation run. The input and output for each stage are presented in Figure 1, which outlines the problem framework.

The stages are executed in sequence and continuously through a feedback loop until the marginal cost of operating an additional pad outweighs the marginal benefit of doing so. At this point a solution is reached that outlines the optimal state of infrastructure, operational costs and passenger waiting times.

Formulation

The problem formulation of the solution method components: vertiport placement, vehicle sizing, and vertiport infrastructure, are presented separately. Throughout the remainder of this section, the variable and parameter definitions used are outlined below.

Indices

i, j	=	nodes
u	=	segment
k	=	vertiport pad type

Sets

V	=	node set
U	=	route segment set
K	=	pad set

Link Parameters

G_{ij}	=	driving time from i to j [h]
L_{ij}	=	expected trip time from i to j [h]
D_{ij}	=	relative demand from i to j [trip]
H_{ij}	=	haversine demand from i to j [km]
p_s	=	flight segment power requirement [W/kg]
l_s	=	flight segment power loading requirement [W/kg]
t_s	=	flight segment travel time

Vehicle Parameters

$s_{p,u}$	=	specific power [W/kg]
$s_{e,u}$	=	specific energy [Wh/kg]
N	=	flight cycles [-]
m_p	=	vehicle payload [kg]
m_b	=	battery mass [kg]
B_U, B_L	=	upper/lower battery level bound [%]
C	=	battery C-rate [%/h]
E	=	battery energy [J]
r	=	reserve battery [%]
R_r, R_d	=	recharge/discharge rate [%/h]
Q	=	required recharge [%]
r	=	recharge time [s]
M	=	max take-off mass [kg]
Q	=	battery capacity [mAh]

Decision Variables

x_{ij}	=	Boolean: open or closes link between two vertiports
o_i	=	Boolean: open or closes vertiport i
c_{ik}	=	Integer: number of servers per type k at vertiport i
z_{ij}	=	Boolean: flight link requirements satisfied

Queuing Parameters

Q_{ij}	=	arrival rate [W/kg]
P_{0ij}	=	probability of no queue [-]
β_c, β_l	=	charging and VTOL pads bound [-]
λ_{qij}	=	queue length [-]
p_{ikl}	=	probability of changing from state k to l at i [-]
W_{qij}	=	waiting time of queue q [s]

Vertiport Placement

The vertiport placement model finds the most optimal vertiport locations in a city given relative demand levels between candidate locations. The model is based on a variant of the uncapacitated p-hub location problem and aims to maximise the total travel time saved in the system relative to driving to quantify the overall benefit to its users. The following modelling simplifications are adopted:

Assumption 1: Driving is the main competitor of air-taxi services. Qualitative air-taxi demand studies (*28, 29*) found autonomous cars to be the biggest competitor to air-taxi services. As such, the objective maximises the total time saved in the system relative to driving.

Assumption 2: Trips are only operated when the factored routing distance lies within a specified bound H_{min}, H_{max}. Vehicles are assumed to fly at a average speed of 242km/h as required by (*30*), and a safety routing routing factor $\mu = 1.42$ is assumed.

Assumption 3: Relative demand levels between vertiports are considered. As (*31*) postulates, absolute demand levels will vary as the service is introduced and are challenging to model. Thus, relative demand levels provide a more accurate depiction of the operational service requirements between vertiports.

Assumption 4: Following (4), air taxi trips must provide over 40% *travel time savings to be considered relative to driving*. Furthermore, travel time savings constitute the main benefit of UAM.

$$\text{maximise} \ \ (G_{ij} - L_{ij})D_{ij}x_{ij} \tag{1}$$

$$\sum_{i \in V} o_i = n \tag{1.1}$$

$$x_{ij} \leq o_j \ \ \forall i,j \in V \tag{1.2}$$

$$x_{ij} \leq o_i \ \ \forall i,j \in V \tag{1.3}$$

$$z_{ij}H_{min} \leq z_{ij}H_{ij} \ \ \forall i,j \in V \tag{1.4}$$

$$z_{ij}H_{ij} \leq z_{ij}H_{max} \ \ \forall i,j \in V \tag{1.5}$$

$$0.6z_{ij}D_{ij} \leq z_{ij}L_{ij} \ \ \forall i,j \in V \tag{1.6}$$

$$z_{ij}\frac{\sum_u^U p_u t_u M}{m_b} \leq z_{ij}s_{e_{max}} \ \ \forall i,j \in V \tag{1.7}$$

$$z_{ij}s_{e_{min}} \leq z_{ij}\frac{\sum_u^U p_u t_u M}{m_b} \ \ \forall i,j \in V \tag{1.8}$$

$$z_{ij}M \max_{u \in U}(l_u) \leq z_{ij}C_{max}s_{e,i}m_b \ \ \forall i,j \in V \tag{1.9}$$

$$z_{ij}\frac{Q}{r} \leq z_{ij}C_{max}s_{e,i}m_b \ \ \forall i,j \in V \tag{1.10}$$

$$z_{ij}\frac{\sum_u^U p_u t_u M}{s_{e_{max}}} - \frac{E_{max} - E_{min}}{N} \leq z_{ij}C_{max}s_{e,i}m_b \ \ \forall i,j \in V \tag{1.11}$$

$$x_{ij} \leq z_{ij} \ \ \forall i,j \in V \tag{1.12}$$

$$o_i = \{0,1\} \ \ \forall i \in V \tag{1.13}$$

$$x_{ij}, z_{ij} = \{0,1\} \ \ \forall i,j \in V \tag{1.14}$$

The objective is outlined by equation (1), which maximises the savings of using the UAM service compared to driving between each origin destination pair. Constraints (1.1-1.3) ensure that n vertiports are opened, and only links between opened vertiports are activated. Note that variables o_i, z_{ij} and x_{ij} are set as Boolean by (1.13) and (1.14).

Constraints (1.4-1.11) outline the operational conditions that must be met for a link to be usable in the network. As specified by assumption 2, (1.4) and (1.5) state that the length of activated paths are bounded by $[H_{min}, H_{max}]$ bounds. Constraints (1.6) constitutes assumption 4, ensuring that links activated provide at least 40% travel time savings with respect to driving.

The remaining constraints relate to the vehicle size requirements. The specific energy of the battery must lie within the bounds $s_{e_{min}}$ and $s_{e_{max}}$ given (1.7) and (1.8). Finally, (1.8-1.11) ensure that the battery size satisfy the charging and discharge requirements for each vertiport i. The origin of these relationships are described in the next section.

Vehicle Sizing

The vehicle sizing stage aims to minimise the battery mass required to undertake a trip defined by its mission profile. As observed in equations (1.8-1.11), the size of the battery and its recharge capability determine the viability of the UAM network. The methodology developed in this section assumes that 50% of the vehicle mass is attributed to structure and the remaining 50% to battery and payload as informed by (*18*). Thus, the maximum take-off mass (M) is expressed as follows:

$$M = 2(m_b + m_p) \tag{2}$$

Determining the battery mass requires the estimation of the operational power requirements. Using the output specified by the vertiport location algorithm, we select the trip with highest power requirements and model the battery to ensure operations are feasible for this trip. Thus, the energy requirement for a trip is calculated using equation (3).

$$E_t = \sum_{u}^{U} (p_u t_u) \tag{3}$$

Given a maximum specific energy $e_{s_{max}}$ parameter which determines the amount of energy produced per unit mass of battery, the minimum battery mass m_b that satisfies the design mission profile is given by 4.

$$m_b = \frac{M \max_{u \in U} (l_u)}{e_{s_{max}}} \tag{4}$$

Rearranging this equation leads to the following expression for battery mass:

$$m_b = \frac{2m_p \cdot \max_{u \in U} (l_u)}{e_{s_{max}} - 2\max_{u \in U} (l_u)} \tag{5}$$

Consequently, the specific energy e_s required to undertake a trip can be written as:

$$e_s = \frac{E_t}{m_b} \tag{6}$$

Uber's operational requirements (*30*) requires vehicles to be able to undertake the largest trip in the system for 3 hours continuously while only charging for 5 minutes between trips. This minimises the opportunity costs associated with vehicles servicing less demand due to charging.

Consequently, loiter times would lead to increased recharge rates as the vehicle maintain flight for longer periods. If the recharge rate exceeds to maximum allowable C-rate for Li-Ion batteries, a vehicle will not satisfy Uber's requirement. As such, minimising loiter time not only minimises lost opportunity costs, but also reduces the peak time requirement for each vehicle. The battery level E_{n+1} after charging E_{charge} following a trip E_n that requires an energy of E_{trip} can be obtained using the following arithmetic sequence:

$$E_{n+1} = E_n - E_{trip} + E_{charge} \tag{7}$$

Let Δt be the duration of one cycle during rush hour, E_{min} be the required battery level at the end of rush-hour and E_{max} be the battery level at the beginning of rush-hour. The number of cycles during that window is given by $N = \frac{\Delta t}{T}$ cycles, where T is the time to undertake the largest trip in the system. To reach a desired battery level E_{min} at the end of rush hour, the required energy recharge R is given by:

$$R_r = E_t - \frac{E_{max} - E_{min}}{N} \tag{8}$$

$$E_{max} = 2(m_b + m_p) e_s B_U \max_{u \in U} (l_u) \tag{9}$$

$$E_{min} = 2(m_b + m_p)e_s B_L \max_{u \in U}(l_u) \tag{10}$$

As the battery discharges rapidly and unpredictably when it falls below its 10% threshold ($B_L = 0.1$), this limit constitutes a lower bound that should never be reached, in addition to any charge reserves required. Furthermore, the top 20% take significantly longer to charge and are usually ignored in UAM models ($B_U = 0.8$) (*32*). Thus, 30% of the battery capacity is to never be consumed, which is represented mathematically by scaling the battery capacity by a factor $B_f = 0.7$.

The required recharge rate R to satisfy Uber's requirement given a charging time t_r is given by:

$$R = \frac{R_r}{r} \tag{11}$$

Li-Ion's batteries dictate the maximum charge/discharge rate a battery can sustain. This is added as a hard constraint in the vertiport placement model. The maximum discharge rate given a battery capacity B_c is given by:

$$R_d = \frac{2\max_{u \in U}(l_u)(m_b + m_p)}{Q} \tag{12}$$

Infrastructure Specifications

Given a vertiport configuration, the queuing theory model finds the number of landing, charging, storage and take-off pads which balance the waiting times in the system, as well as the operating and infrastructure costs. These waiting times are fed back into the vertiport placement model until the marginal cost of removing an additional vertiport outweighs the marginal benefit.

Vertiports can be modelled as open-network multi-server queuing systems using Jackson's theory (*33*), which assumes independence of arrival rates at each server in the steady state. However, waiting times at each pad are not independent of each other in congested scenarios. In practice, congestion will propagate upstream, from storage pads to charging pads, and from charging pads to landing pads. This scenario infeasible from an operational and service level perspective as loiter times will exceed the predefined battery specifications and passenger waiting times will not be tolerable.

To avoid the aforementioned scenario, the service rate at each pad must exceed the vehicle arrival rate. Assuming a Poisson distributed arrival rate, and a service rate that exceeds arrival rate rate, a steady state configuration can be reached. In this case, the arrival rates and queue sizes at each server can be assumed to be independent of the other servers in the system.

However, UAM demdand is expected to have a bi-modal daily distribution, suggesting that the system will not operate in a steady state configuration. Nevertheless, designing the system to a steady state configuration with a similar behaviour to rush hour conditions will lead to a configuration that is feasible for lower demand levels. Consequently, queuing theory can be used to optimise the number of landing, charging, storage and take-off pads assuming a steady state, rush-hour configuration.

The arrival rates at each vertiport, transition probabilities between pads of a given vertiport and the service rate of each pad are obtained by running an agent-based model for a very large number of pads. In this scenario, all demand is satisfied. This enables us to study the behaviour of each vertiport independently. At each vertiport, the vehicles are routed to different pads in a probabilistic manner.

Given the rush hour arrival rate Q_{ij}, the service rate μ_{ij} of pad j at vertiport i and the set of probabilities p_{ijz} of a vehicle in vertiport i follows:

$$\frac{Q_{ij}}{\mu_{ij}m_{ij}} < 1 \tag{13}$$

If steady state conditions are not satisfied, the queue size is expected to increase indefinitely, leading to the aforementioned congested scenario. Given an arrival rate Q_{i1} at the landing pads of vertiport i, the transitional probabilities p_{ijk} of a vehicle transitioning from pad type j to k at vertiport i, the arrival rate Q_{ij} at each pad j of vertiport i is calculated as follows:

$$Q_{ij} = \sum_{z}^{Z}(p_{ikj})Q_{i1} \tag{14}$$

For each pad j of vertiport i, the utilisation ρ_{ij} is defined as:

$$\rho_{ij} = \frac{Q_{ij}}{\mu_{ij}} \tag{15}$$

The probability P_{0ij} of an empty queue at pad j of vertiport i is calculated as follows:

$$P_{0ij} = \sum_{n=0}^{c-1}[\frac{\rho_{ij}^{n}}{n!} + \frac{\rho_{ij}^{c}}{c!(1-\frac{\rho_{ij}}{c})}]^{-1} \tag{16}$$

The average length of the queue λ_{qij} is given by:

$$\lambda_{qij} = \frac{P_{0ij}\rho_{ij}{}^{c}\frac{\rho_{ij}}{c}}{c!(1-\frac{\rho_{ij}}{c})^{2}} \tag{17}$$

Finally, the waiting time W_{qij} at pad j of vertiport i is given by:

$$W_{qij} = \frac{\lambda_{qij}}{Q_{ij}} \tag{18}$$

Waiting times directly affect the vertiport placement and vehicle sizing models. Larger wait times requirements reduce the travel time savings relative to driving and overall benefit of the UAM network. Longer loiter times lead to larger battery sizes, which can make some trips unfeasible due to the recharge requirements. Larger vehicle size and increased energy depletion due to loiter increase the cost of vehicle procurement, charging and maintenance. Consequently, waiting times heavily influence the operational feasibility of the UAM network and the system costs.

Operational and Infrastructure costs

The operating costs in this study are composed of: vehicle maintenance, vehicle insurance, pilot salary, energy costs, battery procurement and life cycle costs, indirect costs, carbon tax and opportunity costs. The values and reference for all the parameters introduced in this section will be outlined in the Case Study section.

Maintenance costs are calculated assuming a specific rate of maintenance requirements per flight-hour. Vehicle acquisition costs are based on the vehicle maximum take off weight, with insurance consisting of a percentage of the total vehicle acquisition cost. Crew costs include all pilot salaries given the number of vehicles required. Energy and battery costs are determined based on the estimated average flight time which includes loitering, with battery life-cycles obtained as per (*28*).

Indirect costs include credit card fees, overhead for commercial aviation, taxing, landing fees and others and are assumed to represent 10% of the total costs. Opportunity costs are calculated based on the proportion of waiting time T_w from the total trip time T_t:

$$O = \alpha \frac{T_w}{T_t} C_o \tag{19}$$

where α corresponds to the operating margin (*29*), and C_o to the operational costs.

The main infrastructure cost components are associated with the landing, charging, storage, and takeoff pads. This includes the cost of piling, composite decking as well as the carrier terminal cost. These costs are used to determine the infrastructure cost of different vertiports deployment scenarios. Additionally, a high voltage charger cost of is included for each charging pad. The take-off and landing pads for eVTOL vehicles are comparable to a helicopter pad.

Feedback Loop

Increasing the number of landing, charging and storage pads will lead to improve waiting times and reduce opportunity costs provided the operational requirements are satisfied. Despite these improvements, it will also increase the infrastructure costs.

This interrelationship is captured using a feedback mechanism, which collects the output of the vertiport infrastructure model and updates the constraints of the vertiport placement model based on the requirements of the vertiport infrastructure. The feedback loop aims to find a balance between the infrastructure, operational costs and passenger waiting times. The number of pads is decreased with every iteration until the marginal cost exceeds the marginal benefit or the problem becomes infeasible.

CASE STUDY

The method described in the methodology is applied to find the optimal system configuration for a potential deployment scenario in the city of London. This study assumes a five vertiport configuration for the short-term UAM application. To showcase the study's contribution, a baseline model based on current literature is developed which ignores the interdependencies between vertiport placement, vehicle sizing and infrastructure specifications. This baseline is used as a comparison to the integrated approach proposed in this paper. All cost parameters used are presented in Table 2.

Demand Generation

As stated by (*31*), UAM is still in its early stages of development to forecast absolute demand levels for trips within a city. However, using existing transportation data, one can estimate relative demand levels between different areas for the purpose of vertiport placement.

Assumption 1: TfL's Rolling Origin and Destination Survey (RODS) is assumed to give an adequate representation of London's underground travellers' behaviours

The RODS captures important statistics on trips undertaken in the London Underground Limited (LUL). It provides an origin-destination matrix classified by station, zone, and time of day. The data is based on November 2017 counts and abnormal fluctuations in demand due to unusual conditions are neglected (*40*). As such, the RODS is considered to give an adequate representation of London's underground travel behaviours on a typical weekday and will be used to infer air-taxi demand.

TABLE 2 Cost parameters.

Operating costs		
Parameter	Value	Reference
Mechanic salary [$/h]	60	(*28*)
Maintenance time [h]	0.68	(*28*)
Vehicle acquisition [$/kg]	333	(*28*)
Pilot salary [$/h]	100	(*23*)
Pilot yearly flight-hours [h]	500	(*28*)
Energy costs [$/MJ]	0.0492	(*34*)
Emissions rate [kg/MJ]	0.0786	(*35*)
Battery acquisition [$/MJ]	111	(*28*)
Carbon tax [$/kg]	0.0198	(*36*)
Operating margin [-]	0.3	(*7*)
Infrastructure costs		
Vertiport costs [$/$m^2$]	4122	(*37–39*)
High-voltage charger [$]	453	(*4*)

Assumption 2: Each borough can hold at most one vertiport

Most vertiport placement studies have been undertaken in the United States, where the demand is usually aggregated on a census tract level (*31*), (*11*), equivalent in size to London wards. Considering the differences between the United Kingdom's and United States' potential air-taxi market (*41*), it is more adequate to discretise London into larger geographical entities. Further, there are more wards than London underground stations which will result in many OD pairs not having demand associated to them. As a result, a coarser, borough level aggregation was chosen, which produced the candidate presented in Figure 2 and Table 3. One limitation of this approach is that the boroughs of Bexley, Bromley, Croydon, Kingston upon Thames and Sutton, which are not served by underground stations, do not have demand associated to them.

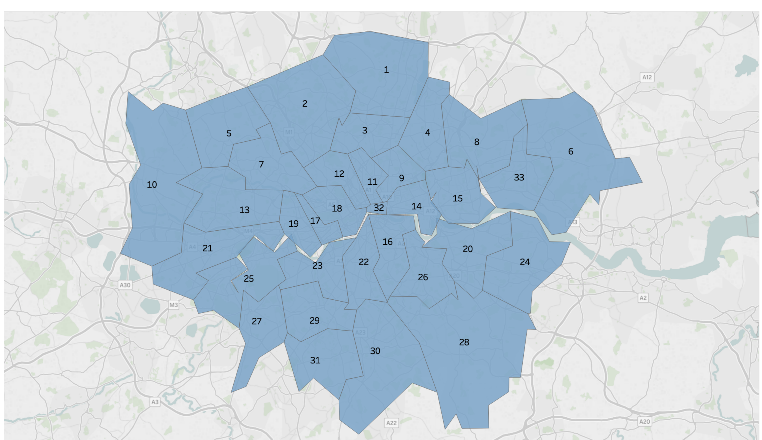

FIGURE 2 London borough map

Assumption 3: Applying (20)'s distance weighing factor to the aggregated RODS demand gives us a good indication of relative UAM demand between boroughs

To represent realistic air-taxi demand levels based on existing transport datasets, (*21*) define a distance weighing function, which is calculated based on the haversine distance d as follows:

$$w_d = \frac{1}{367.8791} d^2 e^{-0.001d^2} \tag{20}$$

The distance weighing factor centres demand around distances of 8 to 20 km: trips that are too short or too long to be attractive by air-taxi have been de-emphasised. The weighted demand distribution is thus more suitable for representing potential air-taxi demand and will be used as an input to the vertiport placement model.

Results

To reflect the current state-of-the-art, the baseline model developed for this study is defined by equations 1-1.7 and 1.12-1.14. Rather, vehicle sizing is undertaken by post-processing the vertiport placement's outputs. The effects of waiting times on the system will also be ignored.

Our holistic model proposed in Section 4, is also used to incorporate the effects of waiting times and vehicle performance into the original vertiport placement model, as well as determining the optimal pad configuration at each vertiport. An initial upper boundary pad configuration of 16 pads per vertiport is used to ensure operational feasibility. This number is reduced until the marginal cost of removing a certain pad outweighs the marginal benefit of doing so, provided the operational constraints are satisfied. To quantify the effects of increasing demand on the system, the model is run for three rush-hour demand scenarios: 50, 150 and 250 vehicles/hour.

FIGURE 3 Vertiport placement results for the baseline and optimal case. Haringey, Westminster and Newham are selected in both cases.

All demand scenarios lead to the same optimal vertiport configuration and vehicle size. In comparison to the baseline model the longest trip in the system is 39% shorter, that being the 14km trajectory connecting Barnet to Westminster. The baseline selects the Brent-Newham connection of 23km as its longest trajectory.

In spite of the shorter travel distances, the battery size in the holistic model is 6% larger than in the baseline case. This suggests that the vehicle sizing model is unable to produce a feasible battery size for this trip, highlighting a key limitation of existing methods.

Figure 5 highlights that, although both vehicle configurations are effectively able to fly the largest trip in the system, the baseline configuration does not satisfy Uber's operational require-

TABLE 3 Borough candidate vertiport location.

Borough	Latitude	Longitude
Enfield	51.6538	-0.0799
Barnet	51.6252	-0.1517
Haringey	51.6	-0.1119
Waltham Forest	51.5908	-0.0134
Harrow	51.5898	-0.3346
Havering	51.5812	0.1837
Brent	51.5588	-0.2817
Redbridge	51.559	0.0741
Hackney	51.545	-0.0553
Hillingdon	51.5441	-0.476
Islington	51.5416	-0.1022
Camden	51.529	-0.1255
Ealing	51.513	-0.3089
Tower Hamlets	51.5099	-0.0059
Newham	51.5077	0.0469
Southwark	51.5035	-0.0804
Kensington and Chelsea	51.502	-0.1947
Westminster	51.4973	-0.1372
Hammersmith and Fulham	51.4927	-0.2339
Greenwich	51.4892	0.0648
Hounslow	51.4746	-0.368
Lambeth	51.4607	-0.1163
Wandsworth	51.4567	-0.191
Bexley	51.4549	0.1505
Richmond upon Thames	51.4479	-0.326
Lewisham	51.4452	-0.0209
Kingston upon Thames	51.4085	-0.3064
Bromley	51.4039	0.0198
Merton	51.4014	-0.1958
Croydon	51.3714	-0.0977
Sutton	51.3618	-0.1945
City of London	51.5155	-0.0922
Barking and Dagenham	51.5607	0.1557

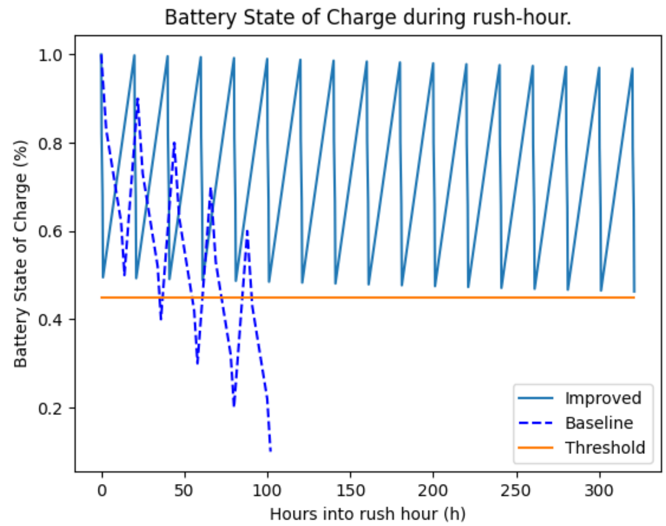

FIGURE 4 Battery state of charge variation during peak-time.

ments under reasonable C-rate assumptions. In fact, battery levels deplete below reserve after only undertaking 2 trips while charging at a 5C rate. The holistic model provides sufficient capacity to undertake the longest trip in the system continuously for 3 hours while only charging for 5 minutes at a 4.8 C-rate.

With notion of the effects of the pad configuration on waiting times, and hence operational costs, the holistic model can also be used to determine the optimal pad configuration at each vertiport.

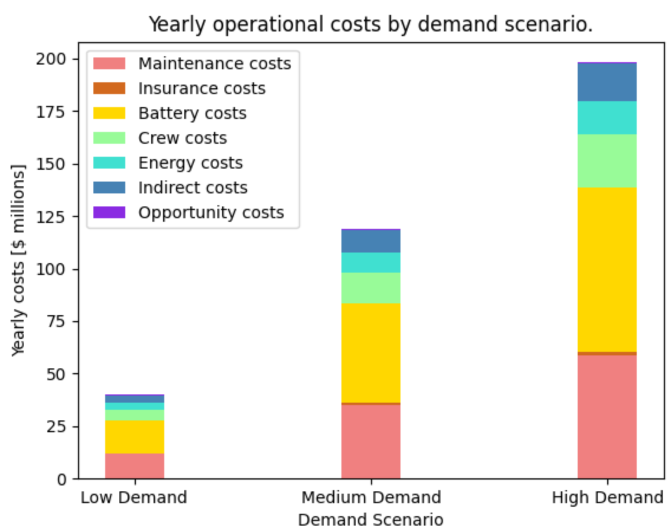

FIGURE 5 Yearly operational costs.

The yearly operational cost is £198 million for the 250 vehicle/hour scenario, compared to £119 and £40 million in the 150 and 50 vehicle/hour scenario, respectively. Nevertheless, the

TABLE 4 Vertiport infrastructure requirements and costs.

Scenario	Low-Demand	Medium-Demand	High-Demand
Number Landing Pads [-]	16	25	34
Number Charging Pads [-]	16	29	38
Number Take-off Pads [-]	11	22	29
Waiting Time Proportion [%]	3.1	0.91	0.56
Landing Pads Cost [$ million] (% of total)	4.39 (47)	6.86 (42)	9.33 (43)
Charging Pads Cost [$ million] (% of total)	1.85 (20)	3.35 (21)	4.39 (20)
Take-off Pads Cost [$ million] (% of total)	3.02 (32)	6.04 (37)	7.96 (37)
Total Infrastructure Cost [$ million]	9.26	16.25	21.69

operational cost breakdown is similar for all scenarios, with batteries, vehicle maintenance and crew incurring the largest costs.

It is also interesting to note that opportunity costs are minimal in all scenarios. In fact, total waiting times remain below 5% of the total flight time in all optimal configurations, with 150 and 250 vehicle per hour demand scenarios yielding waiting times that constitute under 1% of the total flight time. Waiting times increase the energy, opportunity and maintenance costs, leading to greater marginal costs that out weight the benefit of removing a vertiport pad.

Due to the Li-Ion's battery life and price ranges, the battery costs are the highest operational cost component, which is in line other studies (*7*). Improvements in battery performance thus offers significant cost reduction opportunities. (*28*) assumption of 33 minutes per flight hour for maintenance makes associated costs significant. Further, automation has the opportunity to eliminate pilot costs, but will lead to additional costs which should be quantified.

Increasing peak hour demand from 50 to 150 and 250 vehicles/hour leads to a 76 and 130% increase in the total number of pads. Under all conditions, a larger number of charging pads are required compared to the other types. This makes intuitive sense due to the longer service time of charging pads. Further, there are more landing pads than take-off pads in all scenarios, suggesting that marginal cost of removing a landing pad is larger than the one associated with removing a take-off pad.

The yearly infrastructure cost is £21.7 million for the high demand configuration, 134% larger than the lower demand scenario (£9.5 million). Although all configurations require more charging pads than any other pad type, landing pads account for the highest proportion of infrastructure costs as shown in Table 4.

It is interesting to note that operating costs are orders of magnitude larger than infrastructure costs in both scenarios, strengthening the notion that, if retrofitted into existing infrastructure, UAM offers significant cost advantages compared to other transport modes.

DISCUSSION

The study demonstrates the importance of adopting a holistic approach to UAM network design. Its major contribution lies in the development of a method that optimises the main components of UAM systems, while also considering the inter-dependencies between them. By integrating vehicle sizing and performance constraints into the vertiport placement model, the proposed methodology generates a vertiport configuration that satisfies Uber's peak time requirements.

In contrast, the baseline model yields an infeasible solution that is only detected during post-processing. A potential solution is to reduce the number of opened links between the network in order to reduce the peak demand at the vertiports, but this solution will result in a suboptimal UAM network.

Our results show that under low waiting times, battery acquisition and replacement cost are the largest operating cost component. Nevertheless, opportunity costs quickly dominate when waiting times increase, making UAM networks unsustainable. Thus, UAM operations should be designed to operate under minimal turnaround times.

Another interesting insight is that operating costs grow at a faster rate than infrastructure costs when waiting times increase. Therefore, it is advisable to design vertiports to accommodate near 0 theoretical average waiting times at rush-hour. Loiter times lead to the largest increases in operational costs. Not only do they lead to opportunity cots, but they also deplete additional energy, therefore requiring larger batteries and larger charging times.

Sub-system level interactions largely affect the wider UAM network. Increases in waiting times lead to changes in network configuration, operating costs and battery requirements which can make the system unfeasible. Waiting times are heavily dependent on the configuration of pads at each vertiport. Consequently, feedback loops can be used to model the effects of sub-system interactions on the wider UAM system to a reasonable degree.

In spite of these findings, there are several limitations with the approach in this study. The demand modelling is on RODS (*40*) which only consider trip undertaken in the London Underground. The model can be improved by considering other modes of transport and including a logit decision model based on the utility parameter of each mode (*42*). This includes analysing the effects of different pricing schemes in UAM demand as well as queue management.

Furthermore, multi-mode trips, where UAM can be used to complement existing transport modes, are ignored in this study. The safety routing factor *mu* specified in Assumption 2 simplifies the potential effects of air traffic management and noise in the routing of eVTOLs and the configuration of vertiports. Finally, incorporating stochastic travel times, waiting times, and demand levels would provide a more robust network, particularly when incorporating weather effects on demand and flight times.

CONCLUSIONS

This study proposes a holistic approach to optimising UAM networks by considering sub-system interactions on the wider UAM network. The methodology contains three main components: a vertiport placement model, a vehicle sizing process, and a infrastructure queuing model. The latter can be modelled using multi-server open network theory by considering a rush-hour, steady state demand configuration, and its outputs are used to modify the constraints of the vertiport placement model. This approach overcomes the speed limitations related to simulation-optimisation approaches that could be used with the existing agent-based models in the literature.

The method is applied to find the configuration that optimises operational, infrastructure costs as well as service times for the city of London under different demand levels. Results show that UAM systems could effectively be deployed in small scale, with low turnaround times. The findings show that operational costs significantly increase with waiting times, and as such these should be reduced under all circumstances, particularly at higher demand levels. Thus, vertiport design approaches not considering vertiport congestion will lead to suboptimal or infeasible configurations, as was the case with the baseline approach used in this study.

Further work is required to improve the demand modelling to include a logit decision model that considers competing transport modes and multi-modal trips. Moreover, travel times, waiting times, and demand could be modelled stochastically. With the addition of pricing models, these changes would allow the determination of expected profit margins and optimal investment strategies.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: Khalife, Slim, Escribano Macias and Angeloudis carried out the study conception and design, Escribano Macias, Slim and Khalife developed the models and analysed the results. Escribano Macias and Khalife prepared the manuscript. All authors have reviewed the results and approved the final version of the manuscript.

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