1 **DEMAND MODELLING AND OPTIMAL VERTIPORT PLACEMENT FOR**
2 **AIRPORT-PURPOSED EVTOL SERVICES**
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1 ABSTRACT

2 Recent technological advances have only recently made Urban Air Mobility feasible as a realis-
3 tic alternative to existing transport modes. Despite the growing interest, this disruptive service
4 requires accurate strategic investments to ensure its viability in the short- and long-term. While
5 airports have been identified as potential sites for vertiports, extending operations to the urban rest
6 of the urban landscape is still an active area of research. To date, this problem has been addressed
7 through eVTOL demand modelling and operations separately, with a complete breakdown of costs
8 seldom considered. This research proposes a holistic approach to maximise returns of investment
9 to ensure commercial viability of the UAM network. In doing so, this paper integrates a demand
10 binary logit model and an operations model to solve the hub location problem. A case study based
11 on South East England, which connects the central London and its surrounding cities with the UK's
12 largest airports: Heathrow and Gatwick. Our findings suggest that networks with five vertiports,
13 eVTOL prices 1.7 times that of taxis, 2 minutes waiting time, operated using two-seater short range
14 vehicles would result in maximum returns. Further analysis indicates that the corresponding ver-
15 tiport placement mainly included low land cost zones close to very high demand zones, and city
16 periphery zones acting as 'park and ride' stations, with their combination resulting in a return of
17 investment three times larger than typical investing indexes.

18   *Keywords:* Urban Air Mobility, Discrete Mode Choice Modelling, Vertiport Placement,
19 eVTOL operations, Genetic Algorithm

INTRODUCTION

The average Londoner loses over 150 hours due to congestion every year (*2*). This value is only expected to rise in the future given that 68% of the world's population will be living in urban areas by 2050 (*3*). A particularly promising approach for reducing the travel times and increasing the reliability of urban trips lies in utilising the urban airspace through Urban Air Mobility (UAM), which enables electric Vertical Take-off and Landing vehicles (eVTOLs) to operate as air-taxis bypassing ground congestion.

Being a disruptive technology, determining actual demand levels for this mode is particularly challenging. The latter has become more and more important recently as manufacturers and operators rush to prove to authorities its viability and benefits in urban areas. Indeed, during the last decade over 70 eVTOL manufacturers were established (*4*) and $1 billion were invested into UAM by 2018 (*5*). Nevertheless, these investments have yet to be backed up by a concrete demand and cost modelling study showcasing the viability of this technology as well as the potential return on investment.

Previous research has already identified airports as optimal locations for vertiports due to available space (*6*) and potentially high eVTOL demand (*7*). The latter coupled with the fact that airport-purposed trips have specific requirements related to travel time reliability, makes eVTOL shuttle services between airports and urban areas its most promising application.

Despite this findings, it is still crucial to forecast the potential return on investments of UAM strategies to assess the commercial viability of this technology. In doing so, a holistic perspective of UAM network design is required that considers demand modelling, vertiport placement, vehicle sizing and infrastructure requirements, operational constraints and investment costs. While our literature review reveals that previous research has been carried our on this topic, to date, no paper has simultaneously considered demand choice modelling and UAM network design to evaluate different pricing schemes and their effect on the expected demand and network configuration.

To address this gap, this paper develops a demand estimation model, which calculates demand requirements based on geographic and demographic data, and a operational cost model, able to assess the economic viability of eVTOL technology. A genetic algorithm serves to iterate and optimise return of investment of the UAM network. Thus, the contribution of the paper is twofold:

1. To the author's knowledge, this paper is the first to aggregate a thorough demand model with an operational model including both operational and investment cost.
2. It is the first paper to consider vertiport placement based return on investment maximisation and explore its susceptibility to vehicle, network and financial specifications (eVTOL pricing) simultaneously.

In the next section, the relevant literature is reviewed and analysed, followed by an overview of the model including the mathematical formulation of the p-median problem. Thereafter, a section for each sub-model is then presented starting with the demand estimation which then is accompanied by the revenue and cost of operations model. The methodology is then applied to the South East England case study, where results presented for various specifications and then discussed with suggestions for further research.

LITERATURE REVIEW

This review focuses on previous research on demand estimation, UAM operations and cost estimations. A summary of the findings and research gaps is presented at the end of this section.

UAM Demand Estimation

In transportation literature, demand modelling studies generally use a utility function that models users choice of transportation based on surveyed parameters. While simpler approaches have been used in UAM literature (*6, 8, 9*), they disregard any sensitivities from different person groups that influence the mode switch to eVTOL.

(*10*) and (*11*) both used a multinomial (MNL) and panel mixed logit models to estimate the utility function parameters based on an internet-based stated survey in the U.S. However, the models assumed that mode choice was carried out under 'initial' market conditions, thus neglecting time of adoption. (*12*) proposed a similar study applied in the city of Munich, which was later expanded in (*13*) by including an Ordered Logit Model and considering time of adoption.

The utility function parameters were tested using agent-based simulation. (*14*) used MATsim in a complex system with demand modelled through a simple MNL model. However, utility functions included sensitivities based on conventional transport modes, and multimodality was neglected. (*15*) on the other hand considered mutimodality and vertiport placement with the parameters identified in (*15*) used in utility functions. However, results have shown that the estimated utility parameters are very different to expected results.

The reliability of UAM utility function parameter estimation is still needs to be been proven. This suggests that using conventional parameters may be more adequate for mode choice model.

Vertiport Placement

Vertiport placement models aim to determine the optimal location of vertiports and are generally formulated as p-median hub location problems. Within this line of work, (*6*) used a p-median hub location to maximise coverage of taxi trips. (*8*) instead maximises the total travel time savings relative to driving. While in this case time savings are considered, this model does not guarantee optimal demand attraction as the solution can be skewed by very big savings of certain trips. (*16*) resolves this issue by using a neighbouring search method that aimed to minimise the weighted demand distance.

The aforementioned papers ignore UAM operational parameters. (*9*) solves this by including an operation scheduling stage after the vertiport placement model. This, however, results in suboptimal vertiport configurations as the scheduling stage is applied as a post-process, and does not affect the vertiport placement decisions.

The reviewed literature disregards the multimodality of eVTOL trips allowing the simulation of first/last mile segments of trip, or even avoiding the agglomeration of eVTOL ports in the highest demand areas. In terms of objective functions however, not all have considered realistic demand and investment scenarios.

Vehicle Sizing

To this date, NASA's Design and Analysis Rotorcraft (NDARC) has been the basis of the majority of eVTOLs design optimisation mainly through weight and geometry considerations (*17*). Further work in this domain was proposed by (*18*), who considered performance of three different eVTOL types over different ranges, and assessed energy and battery requirements. (*19*) specifically focused on regional air mobility with long range, high payload, and low noise requirements. While both studies estiamte battery capacity requirements, the frequency of replacement was not considered, being one of the main drivers of operational cost.

1   (*20*) presented a UAM vehicle sizing model considering noise emissions, energy perfor-
2   mance and cost. In addition, (*21*) performed a cost analysis on three different eVTOL vehicles, but
3   disregarded battery life cycles and their effect on battery replacement costs.

Integrated approach for operation cost optimisation and demand modelling
5   Following the review of literature, it was quickly identified that demand modelling, vertiport place-
6   ment and vehicle sizing are intrinsically related. This was indeed researched by (*22*), where they
7   propose a N^2-chart that defines the interfaces and connection data between 14 UAM components
8   (Figure 22), with a unique feedback loop between the cost modelling and demand modelling
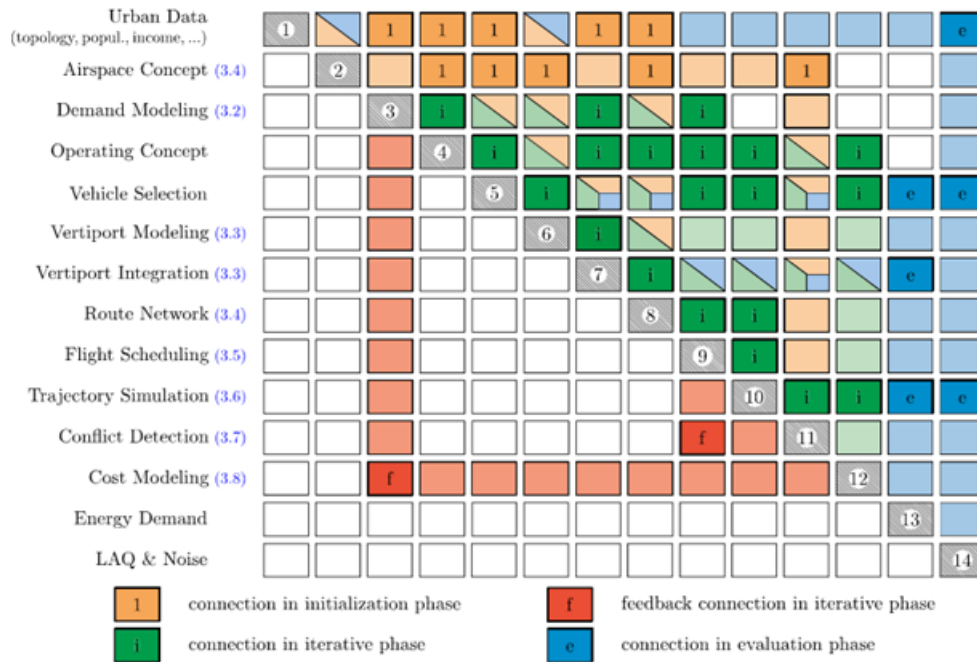9   phases, which to the author's knowledge has not been incorporated before.

FIGURE 1: N^2- chart defining the interfaces and connections between 14 UAM components (Niklaß et al., 2020)

10   The literature review is summarised in Table 1, from which two relevant research gaps
11   were identified. The first identifies that demand modelling, vertiport placement, vehicle sizing
12   and infrastructure requirements were not covered simultaneously, even if a clear relation between
13   them was determined during the review. The second highlights that even if vehicle operational
14   cost where in some cases incorporated in eVTOL vertiport placement, revenue calculation and
15   investment costs were never.
16   To address the gaps identified, this paper proposes a modelling framework to optimise
17   UAM network design considering demand modelling. The algorithm contains two main compo-
18   nents, a binary logit choice model that estimates demand levels based on geographic and demo-
19   graphic characteristics as well as pricing schemes, and a UAM operations model that estimates
20   the commercial viability of the selected vertiports. The workflow is iteratively executed using a
21   metaheuristic that progressively optimises the network configuration based on the final return of
22   investment calculated.

TABLE 1: Literature Review Summary

Focus	Author	Approach	Objective	Features
Demand Estimation	(8)	S	[-]	High Income car users
	(6)	S	[-]	Faster travel times
	(9)	S	[-]	Value of saved travel time
	(10)	MNL,PML	U	US
	(11)	MNL,PML	U	US
	(12)	MNL	U	Munich
	(?)	MNL,OLM	U	Munich; Time adoption
	(14)	AB,MNL	DS	Conventional parameters
	(15)	AB,MNL	DS	Parameters from (12)
	(22)	U-Cast	DS	Air conflict consideration
	This paper	TB,MNL	DS	Airport-purposed
Vertiport Placement	(6)	P	TC	Demand aggregation
	(8)	P	TTS	Traffic; Demand
	(16)	P	WDD	Range comparasion
	(9)	P	TTT	Charging; Scheduling
	(41)	K	ATD	Traffic
	(44)	K	H	Thresholds
	This paper	P	ROI	Traffic;Demand aggregation
Vehicle Sizing	(17)	AN	G,W	Aircraft Layout
	(18)	CO	B,E	Range comparison
	(19)	AN	B,E,N	7-seater RAM vehicle
	(20)	AN	C,E,N	Aircraft Layout
	(21)	CO	C	Operational, Investment
	(22)	CO	C	Cost Linked to Demand
	This paper	CO	B,E,N,C	Cost Linked to Demand

Legend:
Approach: AB - Agent-Based, MNL - Mulitnomial Logit, PML - Panel Mixed Logit, OLM - Ordered Logit Model, P - P-median, K - K-means Clustering, S - Simple, TB - Trip-Based.
Objective: ATD - Access Travel Distance, B - Battery, C - Cost, DS - Demand Simulation, E - Energy, G - Geometry, H - Hubs, N - Noise, ROI - Return on Investment, TC - Trip Coverage, TTS - Total Travel Time Savings, TTT - Total System Travel Time, U - Utility Functions Parameter Estimation, W - Weight, WDD - Weighted Demand Distance.

1 MODEL FRAMEWORK

The framework proposed by this paper aims to maximise the return on investment of vertiport placement through the consideration of airport-purposed eVTOL demand as well as vertiport and vehicle operations and cost. In doing so, eVTOL demand and the UAM system operational strategy are determined using a demand estimation model and a UAM operations model respectively. Figure 2 summarises the model framework.

The model first takes the vertiport configuration as input along with network, financial and vehicle specifications, before moving to both sub-models. The demand estimation model determines eVTOL demand between every city and airport vertiport, using a binary logit model

1 which estimates the probability of selection of each mode for each person group. The sub-model
2 then outputs the eVTOL demand levels and travel time and cost skims matrices.
3   These serve as inputs to the UAM operations model, which calculates the operational and
4 investment requirements. The latter are also used to estimate the revenue based on the financial
5 specifications set. As such, the sub-model combines these variables to estimate and output the
6 return on investment.
7   The presented framework resides within a meta-heuristic that seeks to determine the opti-
8 mal vertiport location based on the financial results of the UAM operations module. The following
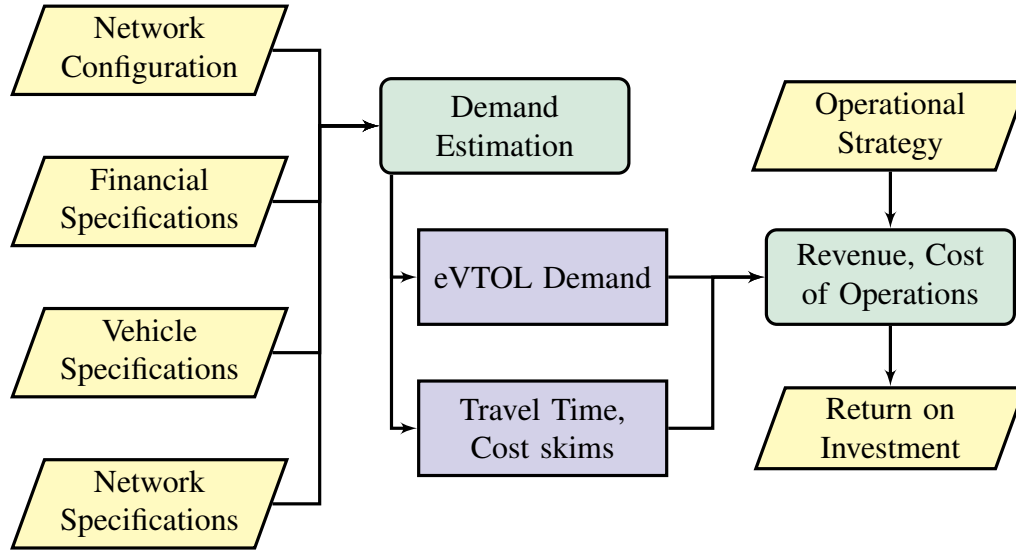9 sections will describe each sub-model in detail.

FIGURE 2: Main model flowchart including both sub-models in green. Inputs/outputs of this model are highlighted in yellow and calculated intermediate variables in blue.

10   The UAM operations modelled in this paper is specified in Figure 3. Airport travellers first
11 use the taxi to arrive to the city vertiport nearest to their residence, then transfer to the eVTOL
12 mode and travel to the their desired airport vertiport.
13   Thus, user travel time consists of effective flight time, vertiport access time, transfer time,
14 and waiting time. If the vertiport is within the same traffic zone, the vertiport access travel time
15 is calculated based on average travel times within the zone. On the other hand, if the vertiport is
16 outside the origin traffic zone, the travel time between both zones is used as calculation. Thereafter,
17 a transfer penalty from taxi to eVTOL as well as the average expected waiting time are added. The
18 eVTOL mode is then is used to travel between the city vertiport to the airport vertiport, where this
19 time no mode changes occur as the destination is directly in the airport.

20 **DEMAND ESTIMATION MODEL**
21 Demand estimation involves analysing the behaviour of travellers due to changes in travel cost,
22 time and other variables that can impact demand. The following assumptions were made:
23   *Assumption 4.1: Taxis are the main competitor of eVTOLs.* This assumption is justified
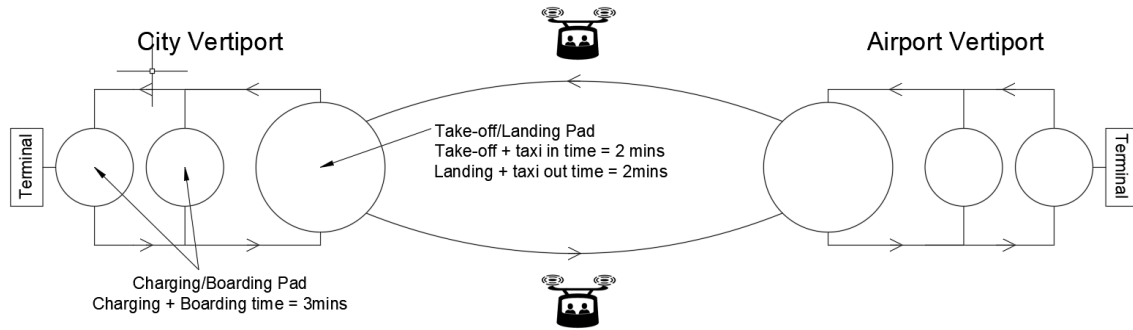24 as relevant person groups involved in airport-purpose trips are most likely to use the taxi service

FIGURE 3: eVTOL operation model illustration

1 due to the complexity of travelling using other modes (airport parking fees, baggage handling,
2 reliability, among others) (*28*).

3   *Assumption 4.2: Induced demand is not accounted for.* While eVTOL would expand the
4 airport catchment area, therefore increasing demand (induced), analysing this will require detailed
5 forecasting and is outside the scope of the research. Also to note, the effects of mode switch to
6 eVTOL on congestion is not considered.

7   *Assumption 4.3: Outgoing and incoming demand for airport travel is assumed to be equal.*
8 This is valid as airports usually have the same amount of departures and arrivals (*24*).

9   *Assumption 4.4: Demand modelling is done using discrete traffic zones.* This means all
10 demand to and from zones will be aggregated at the centroid of the zone.

11   Figure 4 below presents a summary of the algorithm followed in the demand estimation
12 model, split into two sub-algorithms: distribution and assignment.
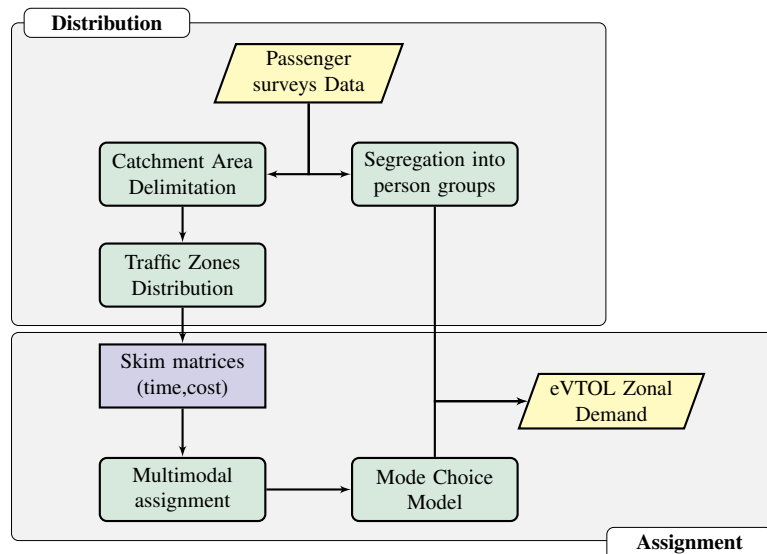

FIGURE 4: Demand estimation model flowchart including the main steps in green. The inputs/outputs are highlighted in yellow and intermediate variables in blue.

1 **Model Initialisation**
2 This step involves the first stages of the model shown in Figure 4 that generate the skim matrices
3 used in multimodal assignment. The process commences by determining the catchment area using
4 data from passenger surveys. This area is then split into multiple traffic modelling zones based
5 on population density. The travel demand between these zones and airports is assigned to several
6 person groups based on income, purpose of travel and residence. The demand is assumed to
7 aggregate at the centroid of each zone.
8   The second step is the calculation of skim matrices, which is carried out for both the taxi
9 and eVTOL transport modes. Taxi travel times matrices are determined using PTV Visum mod-
10 elling software by determining the shortest-path free-flow travel times. To account for congestion,
11 a congestion factor based on the proximity to the city centre and time of day are added as shown
12 in equations (47-48).
13   For travel cost, the standard taxi metering formula is used which can vary if the catchment
14 area is very large. The eVTOL travel time matrices are determined in the same way, but cost is
15 calculated by setting a fixed price and a price per kilometre multiplier.

16 **Multimodal Assignment**
17 The skim matrices produced in the initialisation stage serve as inputs for the multimodal assign-
18 ment, which allocates demand to links while allowing travellers to use multiple transport modes.
19 These paths are determined using a branch and bound algorithm that searches for the minimum
20 travel time path. It is worth noting that in the case of our model, there are two different possible
21 path sequences: a user travels to the vertiport via taxi and then is transported to the airport us-
22 ing eVTOL; and the opposite case where a user leaves the airport to the vertiport closest to their
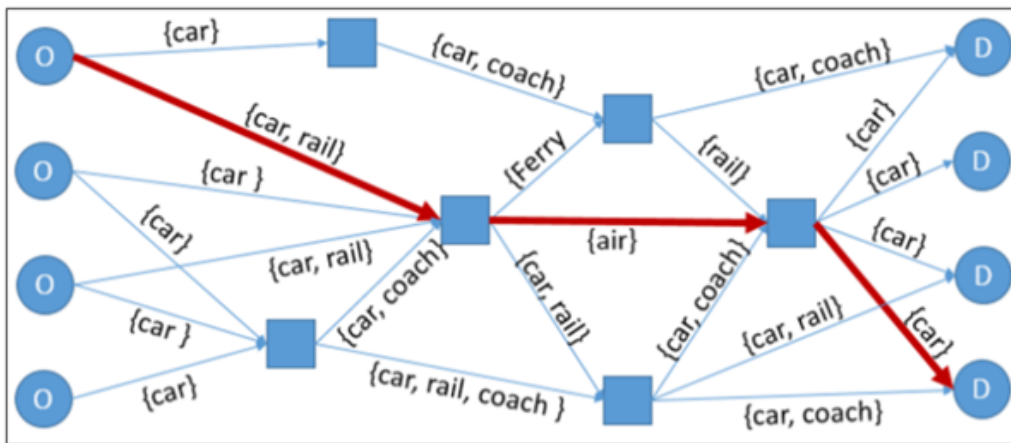23 destination using the eVTOL and travels to their destination via taxi.

FIGURE 5: Multimodal Assignment illustration (PTV AG, 2017)

24 **Mode Choice Model**
25 With the known skim matrices and zone-to-zone demands, this stage estimates the probability of
26 each user to choose a specific mode for travel. Each person group, p, travels from each zone
27 i, to zone j, using either taxi or eVTOL, and the selection of each mode depends on the travel

1 time and monetary costs as defined by the utility functions (1) and (2). The notation conventions
2 summarised below:

Indices   Sets
i, j =   Node $\mathcal{N}$ =   Node set
k, l =   Zone (city, airport zone) $\mathcal{K}$ =   Zone set
p =   Person $\mathcal{P}$ =   Person group set
$taxi, eVTOL$ =   taxi mode $\mathcal{M}$ =   Mode set
$eVTOL$ =   eVTOL mode

Utility Variables
$U_{ij,m,p}$ =   Utility of a trip between zone i and j using mode m for person group p.
$TT_{ij,m}$ =   Travel time between a zone i and a zone j, using mode m.
$TTV_{ij,m}$ =   Travel time variability between zone i and zone j using mode m.
RF =   Reliability factor which represents the importance given to travel time variability.
WT_{eVTOL} =   Passenger waiting time at the vertiport before boarding.
TP_{eVTOL} =   Time penalty to consider vertiport access and mode transfer.
$TC_{ij,m}$ =   Travel cost between zone i and zone j using mode m.

Utility Parameters
$ASC_{m,p}$ =   Alternative specific constant for a mode m, different for each person group p.
$\beta_{m,p}^{TT}$ =   Travel time senstivity parameter for a mode m, different for each person group p.
$\beta_{m,p}^{TC}$ =   Travel cost senstivity parameter for a mode m, different for each person group p.

$$U_{ij,taxi,p} = ASC_{taxi,p} + \beta_{taxi,p}^{TT}(TT_{ij,taxi} + RF \times TTV_{ij,taxi}) + \beta_{taxi,p}^{TC}TC_{ij,taxi} \tag{1}$$

$$U_{il,eVTOL,p|k} = ASC_{eVTOL,p} + \beta_{eVTOL,p}^{TT}(TT_{kl,eVTOL} + 2 \times WT_{eVTOL} + TP_{eVTOL})$$
$$+ \beta_{eVTOL,p}^{TC}TC_{kl,eVTOL} + U_{ik,taxi,p} \tag{2}$$

3   This model assumes that for each person group the error components are identically and
4 independently distributed according to a type 1 Extreme Value (Gumbel) distribution. As such,
5 this implies that the error terms can be translated into a variable μ giving the following expression
6 for mode choice probabilities:

$$P_{(ij,m,p)} = \frac{e^{\mu U_{ij,m,p}}}{\sum_{m \in M} e^{\mu U_{ij,m,p}}} \tag{3}$$

7   Now, by normalising μ to 1 the probability of choosing eVTOL from zone i to an airport,
8 l, given that a vertiport is in zone k, is given as:

$$P_{(il,eVTOL,p|k)} = \frac{e^{U_{il,eVTOL,p|k}}}{\sum_{m \in M} e^{U_{il,m,p|k}}} \tag{4}$$

9   And therefore, the demand for eVTOL from zone i through zone k (where the vertiport is

placed) to the airport, l, can be calculated as follows:

$$D_{eVTOL}^{ikl} = \sum_p D_{il,p} P_{(il,eVTOL,p|k)} \tag{5}$$

The demand for eVTOL between a city vertiport, k and an airport, l is hence calculated as:

$$D_{eVTOL}^{kl} = \sum_i D_{eVTOL}^{ikl} \tag{6}$$

With the mode choice model formulated, the demand for eVTOL between zones can be determined, which are used as inputs on the UAM operations model.

UAM OPERATIONS MODEL

The UAM operations model calculates the costs and revenues of given the demand requirements and UAM network design infrastructure provided in the previous stages. A detailed flowchart of the process is provided in Figure 6. The following assumptions as considered:

Assumption 5.1: Demand for eVTOL travel is uniformly distributed within the hour. While modelling eVTOL operations using an agent-based simulation would be more representative of the on demand aspect of eVTOL, this assumption applies for the implementation of eVTOL as a service to airports (pre-booking flight tickets).

Assumption 5.2: Demand for airport access and egress is uniformly distributed throughout the working hours of the day. This assumption is reasonable for very busy airports where runway slots are full at all times (*26*).

Assumption 5.3: eVTOL battery is swapped after completing a trip. As such, charging time does not need to be calculated and will not vary depending on vehicle specifications.

Following assumptions 5.1 and 5.2, we assume a constant rate of take-offs and landings. Therefore the number of charging of pads per take-off/landing pad, n_{CP} can be calculated using the take-off and landing time, $t_{take-off,landing}$ as well as the charging/boarding time, $t_{charging}$:

$$n_{CP} = \frac{t_{charging} - t_{take-off,landing}}{t_{take-off,landing}} \tag{7}$$

Cost and Revenue Calculation

It is important to note that eVTOL demand will not necessarily be equal in both directions: eV-TOL trips can be assumed to have the same utility as routes in both direction follow the same path, however, the same is not true for taxi trips. For the remainder of this section, the following nomenclature is used:

Parameters

WT	=	Passenger waiting time	GS	=	Passengers group size
TO_{pad}	=	Pad turnover time	T_{max}	=	Maximum pilot working hours
r_{mt}	=	Maintenance rate	r_{CO2}	=	Rate of CO_2 emissions
r_{ins}	=	Insurance Rate	C_{Bat}	=	Mode set
SPL	=	eVTOL mode	$N_{vertiport}$	=	eVTOL mode
r_{me}	=	Maintenance cost	r_{EC}	=	Energy usage cost

r_{ct}	=	Carbon tax cost	r_{bat}	=	Battery cost
S_{pilot}	=	Pilot costs	r_{ind}	=	Indirect cost share
VC	=	Vehicle acquisition cost	$C_{vertiport,pad}$	=	Pad operational cost
$C_{infra,pad}$	=	Pad infrastructure cost	$A_{land,pad}$	=	Land area per pad
$C_{land,sqm}$	=	Land cost	t	=	Corporate tax rate
Q	=	Energy consumption			

Variables

R	=	Revenue	OC	=	Operational cost
IC	=	Investment cost	ROI	=	Return on investment
TC	=	Travel cost	MC	=	Maintenance cost
ISC	=	Insurance cost	PC	=	Pilot cost
EC	=	Energy cost	BRC	=	Battery replacement cost
CT	=	Carbon tax	NDF	=	Noise disturbance factor
ESF	=	Economy of scale factor	D	=	Demand
PP	=	Passenger pool	n_{trips}	=	Number of trips
n_{veh}	=	Number of vehicles	N_{trips}	=	Daily vehicle trips
N_{pads}	=	Number of pads	TH	=	Time headway between vehicles
TT	=	Travel Time	t_{op}	=	Vehicle operational air time
T_{daily}	=	Daily operation hours	EU	=	Energy used
LC_{bat}	=	Battery life cycle	DOD	=	Depth of discharge
$f_{replace}$	=	Battery replacements			

1   We first define the operational parameters that influence the cost and revenue calculations:
2   average passenger pool, number of trips, and number of vehicles required to undertake said trips
3   (8-10).

$$PP^{kl}_{eVTOL,h} = \frac{D^{kl}_{eVTOL,h}}{60} \times WT \times GS \tag{8}$$

$$n^{kl}_{trips,yearly} = \sum_h \frac{D^{kl}_{eVTOL,h}}{PP^{kl}_{eVTOL,h}} \times 365 \tag{9}$$

$$n^{kl}_{veh} = \sum \frac{n^{kl}_{trips,yearly}}{N_{trips,eVTOL,yearly}} \tag{10}$$

We can also define the daily and yearly revenue per city vertiport, k or airport vertiport, l:

$$R^k_{daily} = \sum_l \sum_h [(D^{kl}_{eVTOL,h})(TC^{kl}_{eVTOL})] \tag{11}$$

$$R_{yearly} = (\sum_k R^k_{daily} + \sum_l R^l_{daily}) \times 365 \tag{12}$$

4   Now, we determine the cost of operating eVTOLs which includes: maintenance costs,
5   pilot salary, energy cost, battery replacement cost, energy usage, CO_2 emissions cost, and other
6   indirect costs. Therefore, the total vehicle operating cost on a route from city vertiport, k, to airport
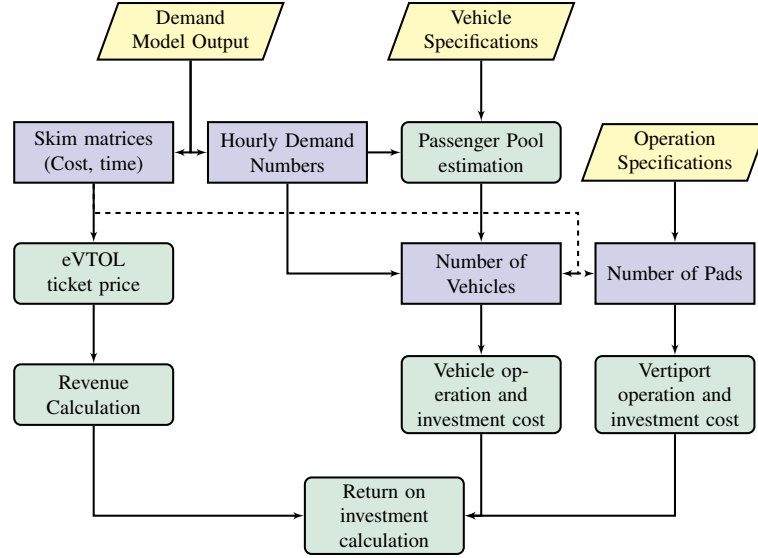7   vertiport, l can be calculated as:

FIGURE 6: Revenue and cost of operations model flowchart including the main steps in green. The inputs/outputs are highlighted in yellow and intermediate variables in blue.

$$OC_{vehicle}^{kl} = (1 + r_{ind})(MC^{kl} + ISC^{kl} + PC^{kl} + EC^{kl} + BRC^{kl} + CT^{kl}) \tag{13}$$

$$OC_{vehicle,yearly} = \sum_l \sum_k OC_{vehicle}^{lk} + \sum_k \sum_l OC_{vehicle}^{kl} \tag{14}$$

1   Where maintenance cost is proportional to the flying hours of eVTOL as per the following
2 equation:

$$MC^{kl} = [r_{me}r_{mt}(t_{op}^{kl})(n_{veh}^{kl})] \tag{15}$$

     The insurance cost is taken as a proportion of the vehicle acquistion cost.

$$ISC^{kl} = r_{ins}n_{veh}^{kl}VC \tag{16}$$

     Pilot salaries and energy costs are calculated based on their total flight hours

$$PC^{kl} = \frac{T_{daily}}{T_{max}}n_{veh}^{kl}S_{pilot} \tag{17}$$

$$EU^{kl} = [(t_{op}^{kl})(n_{veh}^{kl})Q_{Cruise} + n_{trips,yearly}^{kl}(Q_{Take-off} + Q_{Landing})] \tag{18}$$

$$EC^{kl} = r_{EC} \times EU^{kl} \tag{19}$$

3   Battery replacement represents a significant cost to UAM operations due to their limited
4 health. The replacement frequency depends on the life cycle of the battery, which itself is affected
5 by the depth of discharge of each trip.

$$DOD_{trip}^{kl} = \frac{EU_{trip}^{kl}}{C_{bat}} \tag{20}$$

$$LC_{bat}^{kl} = -1666.7DOD_{trip}^{kl} + 3833.3 \tag{21}$$

$$f_{replace}^{kl} = \frac{n_{trips}^{kl}}{LC_{bat}^{kl}} \tag{22}$$

$$BRC^{kl} = f_{replace}^{kl} \times C_{bat} \times r_{bat} \tag{23}$$

An additional CO_2 contribution tax is included based on the battery recharging requirements.

$$CT^{kl} = r_{ct} r_{CO2} EU^{kl} \tag{24}$$

Finally, the last consideration are indirect cost, including credit card fees, air traffic management, delay compensation, which will vary depending on the case. As a general approximation, these can be taken as a percentage of the total vehicle operating cost.

The costs of operating vertiports includes utilities, employment and maintenance. We aggregated these cost by assuming these are proportional to the number of take-off and landing pads, which is calculated by estimating the headway between eVTOL vehicles.

$$TH^k = \sum_l \frac{TT^{lk}}{n_{veh}^{lk}} \tag{25}$$

$$N_{pads,k} = \frac{TO_{pad}}{TH^k} \tag{26}$$

The vertiport operational cost for a vertiport in zone k is given as:

$$OC_{vertiport}^k = N_{pads,k} \times C_{vertiport,pad} \tag{27}$$

Hence, the yearly vertiport operational cost for all vertiport is given as:

$$OC_{vertiport,yearly} = \sum_k OC_{vertiport}^k + \sum_l OC_{vertiport}^l \tag{28}$$

$$OC_{total,yearly} = OC_{vehicle,yearly} + OC_{vertiport,yearly} \tag{29}$$

Investment Costs

Investment costs include all infrastructure or equipment payments required to undertake the operation. In this case, it includes land acquisition costs, vertiport construction costs, and vehicle acquisition costs.

$$IC_{total} = IC_{infra} + IC_{vehicles} + IC_{land} \tag{30}$$

The first component of investment cost is the vertiport infrastructure cost which includes the terminal and airside construction, as well as the equipment needed. Similarly to (27) we assume this is proportional to number of pads in the vertiport.

$$IC_{infrastructure}^k = N_{pads,k} \times C_{infrastructure,pad} \tag{31}$$

$$IC_{infra} = \sum_k IC_{infrastructure}^k + \sum_l IC_{infrastructure}^l \tag{32}$$

Land acquisition cost differs by the land value at each zone designated for vertiport con-

struction:

$$IC_{land}^k = N_{pads,k} \times A_{land,pad} \times C_{land,sqm}^k \qquad (33)$$

$$IC_{land} = \sum_k IC_{land}^k + \sum_l IC_{land}^l \qquad (34)$$

Finally, vehicle acquisition cost is assumed a , this time dependant on the number of vehicles:

$$IC_{vehicle}^{kl} = n_{veh}^{kl} \times VC \qquad (35)$$

$$IC_{vehicle} = \sum_k \sum_l IC_{vehicle}^{kl} + \sum_k \sum_l IC_{vehicle}^{lk} \qquad (36)$$

Noise and Economy of Scale Factors
A noise disturbance factor is included to estimate the additional infrastructure needed to attenuate its impact on the surroundings. This factor is calculated as the ratio of normal city noise loudness and that of the eVTOL during take-off or Landing at a distance of 30 meters:

$$NDF = \frac{2^{SPL_{eVTOL}/10}}{2^{SPL_{CityAverage}/10}} \qquad (37)$$

$$OC_{vertiport,yearly} = OC_{vertiport,yearly} \times NDF \qquad (38)$$

$$IC_{land} = IC_{land} \times NDF \qquad (39)$$

$$IC_{infra} = IC_{infra} \times NDF \qquad (40)$$

Furthermore, to consider the advantage of scaling eVTOL network, an economy of scale factor is applied to all operational and investments costs. To do so we assume that every additional vertiport constructed will reduce costs by 2%:

$$ESF = 0.98^{N_{vertiports}-1} \qquad (41)$$

Therefore the reduced operational and investment cost are calculated as such:

$$OC_{total,yearly} = OC_{total,yearly} \times ESF \qquad (42)$$

$$IC_{total} = IC_{total} \times ESF \qquad (43)$$

Finally, the return on investment can be simply calculated using the following equation:

$$ROI = \frac{(R_{yearly} - OC_{total,yearly})(1-t)}{IC_{total}} \qquad (44)$$

Solution Method
The framework presented in the previous sections is fitted into a Genetic Algorithm (GA) meta-heuristic. GAs have been extensively used in simulation-optimisation problems (*27*) given its

1 ability to solve large and complex mathematical problems. It is an iterative algorithm that seeks
2 to progressively improve the solution through trial and error inspired by the theory of natural evo-
3 lution A common Genetic Algorithm structure involves four main processes: problem generation,
4 population selection, crossover and mutation.
5   Our GA implementation is structured as follows: a random population of vertiport con-
6 figurations is generated based on the network constraints set (range, number of vertiports), with
7 the solution encoded as index-based, meaning the selected solution configuration will include the
8 index of each selected zone. Each configuration is then evaluated using the model described in
9 Figure 2, where the return on investment calculated in equation (44) serves as the fitness value. A
10 tournament selection method compares randomly selected solutions and eliminates the one yield-
11 ing the lowest return of investment.
12   The remaining high performing solutions are modified using crossover and mutation, where
13 crossover combines two solutions by switching a random section of each configuration with the
14 other (2-point crossover), and mutation randomly modifies one of the chosen zones in the configu-
15 ration. The process is repeated until a maximum number of generations set by the user is met (see
16 Figure 7).
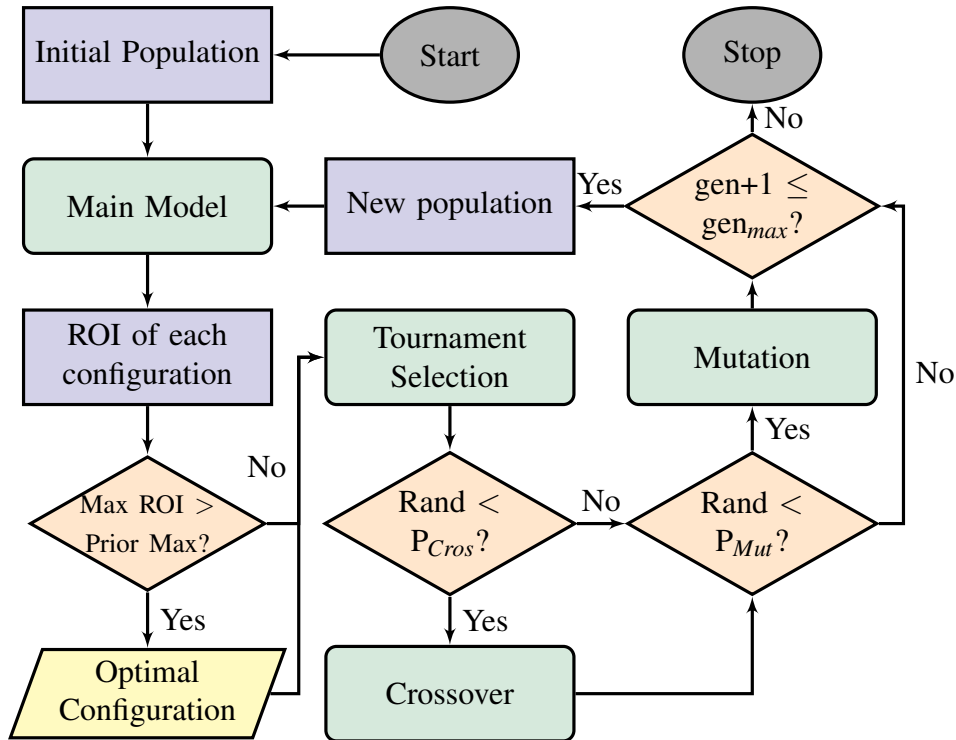
FIGURE 7: Solution method flowchart including the main model and the three main steps of the Genetic Algorithm in green. The output is highlighted in yellow, intermediate steps in blue and decisions taken during the algorithm in red.

17 **CASE STUDY: SOUTH EAST ENGLAND**
18 South East England's main airports (Heathrow and Gatwick) have seen together more than 90
19 million terminating passengers in 2019 (*28*) . While both airports are well-connected to London's
20 transportation network, travel times can vary significantly due to congestion. For this reason, UAM

1 is a highly attractive alternative to provide reliable transportation to and from these airports. This
2 section presents a case study that applies the model developed in this paper to the South East
3 England region and aims to determine the optimal UAM network configuration that maximises
4 return on investment.

5 **Model Setup**
6 We use the latest Civil Aviation Authority passenger survey to determine the number of trips from
7 and to Gatwick and Heathrow. As the resource was last updated in 1998 (*28*), the values were
8 linearly extrapolated based on the increment of the population to obtain an approximation of re-
9 cent quantities (pre-Covid19). Based on the respondents' information presented in the survey, the
10 following person groups were identified:
        1. BMUK: Business Medium income UK residents.
11   2. BHUK: Business High income UK residents.
12   3. BMF: Business Medium income Foreign travellers.
13   4. BHF: Business High income Foreign travellers.
14   5. LMUK: Leisure Medium income UK residents.
15   6. LHUK: Leisure High income UK residents.
16   7. LMF: Leisure Medium income Foreign travellers.
17   8. LHF: Leisure High income Foreign travellers.
18
19   The survey revealed that less than 20% of passengers visiting London's airports originate
20 from outside South East England (see Figure 8), as such this case study will focus solely on the
21 demand that originates South East of England, including Greater London. The region is split into
22 South England counties and two Greater London regions as per Figure (9). The demand at each
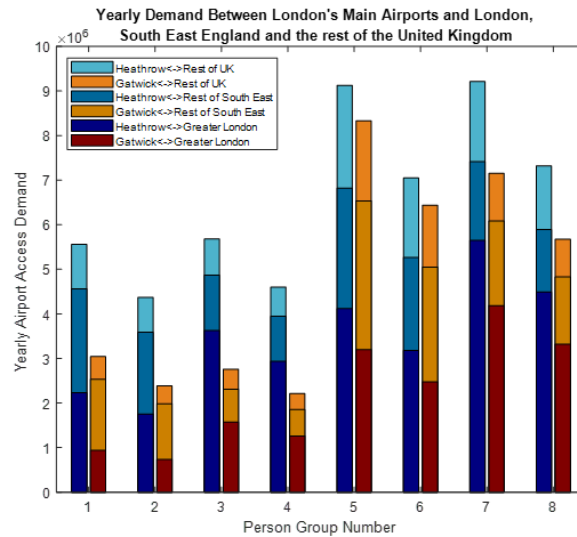23 county was allocated to cities with over 80,000 residents.

FIGURE 8: Yearly demand between London's main airports and UK's relevant regions

24   We then incorporated the ONS survey data (ONS, 2020) which segregates population by
25 income, to discretise the residents into medium and high income groups. One should note that
26 the CAA reports present a significantly higher average income per user compared to the average
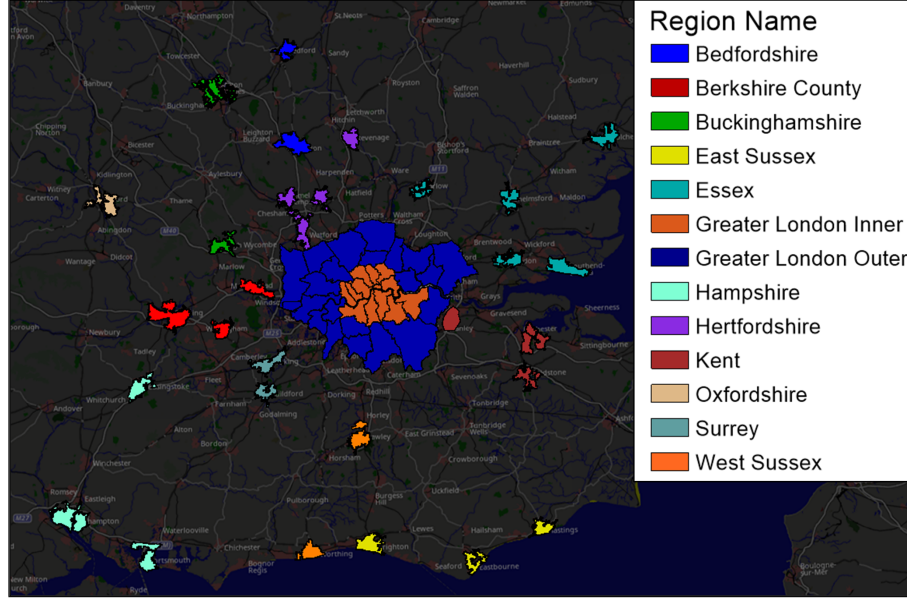
FIGURE 9: South East England demand zones spatial distribution

1   resident in the South East region. To accommodate such disparity, high income percentages were
2   increased, so that the average matches the CAA survey. Hence, Figure 10 shows the corrected ori-
3   gin of travellers per hour (medium and high income only), heading towards Heathrow or Gatwick,
4   used as input for the demand model.
5   With the origin-destination demands calculated, the last step of model setup involves the
6   network implementation and skim matrices calculation, done for both taxi and eVTOL transport
7   modes. Taxis are assumed to utilise the transport network shown in Figure 12 which includes
8   highways, primary roads and main secondary roads that connects zone centroids with highways.
9   To account for congestion, the following equation is implemented to modify taxi travel time:

$$TTC_{ij,h} = TT0_{ij} \times \alpha_{proximity,ij} \times \beta_h \tag{45}$$

10   Where $TT0_{ij}$ is the free-flow travel time and $\alpha_{proximity}$ is the congestion factor based on the
11 distance from the city centre of London, calibrated using Google Maps estimates:

$$\alpha_{proximity,ij} = \begin{cases} 2.5 & if \quad \frac{d_{ic}+d_{cj}}{2} < 20km \\ 2 & if \quad \frac{d_{ic}+d_{cj}}{2} > 20km \ \& \ < 40 \\ 1.5 & if \quad \frac{d_{ic}+d_{cj}}{2} > 40km \end{cases} \tag{46}$$

12   With d_{ic} and d_{cj} being the distance of the origin and destination zones from the city cen-
13 tre. β_h is based on the time of day, h, shown in Figure 11. Finally, based on the average travel
14 time variability calculated using Google Maps, we determined that the variability represented ap-
15 proximately 20% of the congested travel time. In terms of taxi pricing, we determined that prices
16 decrease for regions outside Greater London, and therefore the following taxi pricing scheme (47-
17 48) were defined based on current datasets (TFL, 2021).

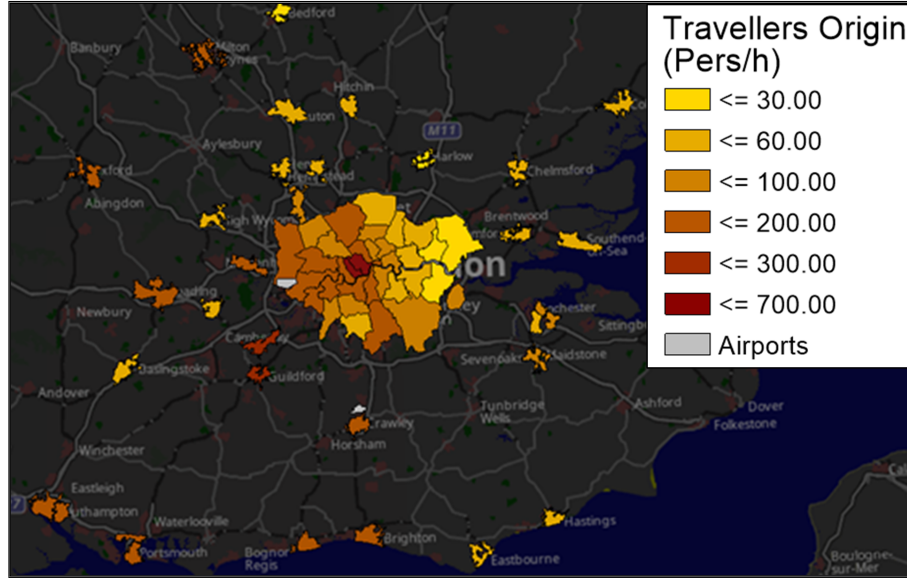$$Fixed_{price,taxi}[\pounds] = 3 \quad for \quad anydistance \tag{47}$$

FIGURE 10: Origin of airport-purposed trips (Destination is equivalent)

$$Variable_{price,taxi}[£/km] = \begin{cases} 2 & if \quad \frac{d_{ic}+d_{cj}}{2} < 20km \\ 1.5 & if \quad \frac{d_{ic}+d_{cj}}{2} > 20km \, \& < 40 \\ 1 & if \quad \frac{d_{ic}+d_{cj}}{2} > 40km \end{cases} \tag{48}$$

1 Conversely, the eVTOL network assumes straight connection between each zone and each
2 airport (Figure 13), so no routing constraints are formulated. Furthermore, the network operation
3 considers no congestion at the vertiport, but a waiting time of 2 minutes and transfer penalty of
4 7.5 minutes were included. For eVTOL pricing, fixed and variable (price per kilometer) price
5 parameters were calculated based on those set for taxis using a user defined price multiplier, *PM*,
6 as denoted in (49-50).

$$FP_{eVTOL} = FP_{taxi} \times PM \tag{49}$$

$$VP_{eVTOL} = VP_{taxi} \times PM \tag{50}$$

7 **Demand Estimation Model Specifications**
8 The utility function parameters were retrieved from (*14*), however to consider the different person
9 groups and trip purpose, different value of times were considered. Based on the latter, the utility
10 function parameters were extrapolated to match the values of times of each person groups. As
11 such, the final derived parameters are presented in Table 2.
12 Based on the final obtained utility function parameters, it is worth mentioning that high
13 income business foreign passengers are most sensitive to increases in travel time. This coincides
14 with Garrow et al. (2020) and Al Haddad et al (2020)'s findings as foreign travellers have less time
15 to spend in the country, and being of high income and on a business trip makes their time very
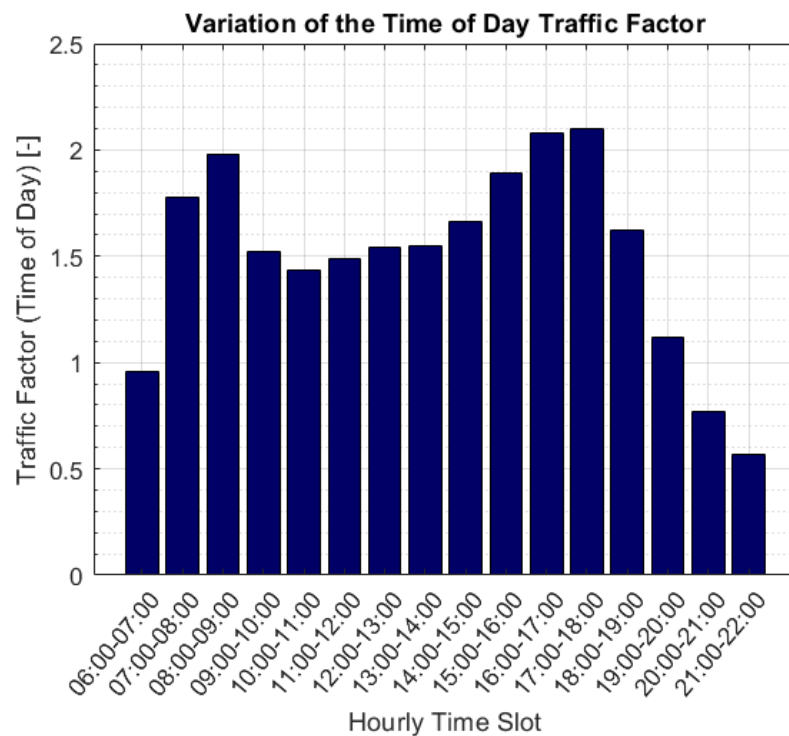16 valuable.

FIGURE 11: Time of day traffic factor variation, β_h (DfT, 2021a)
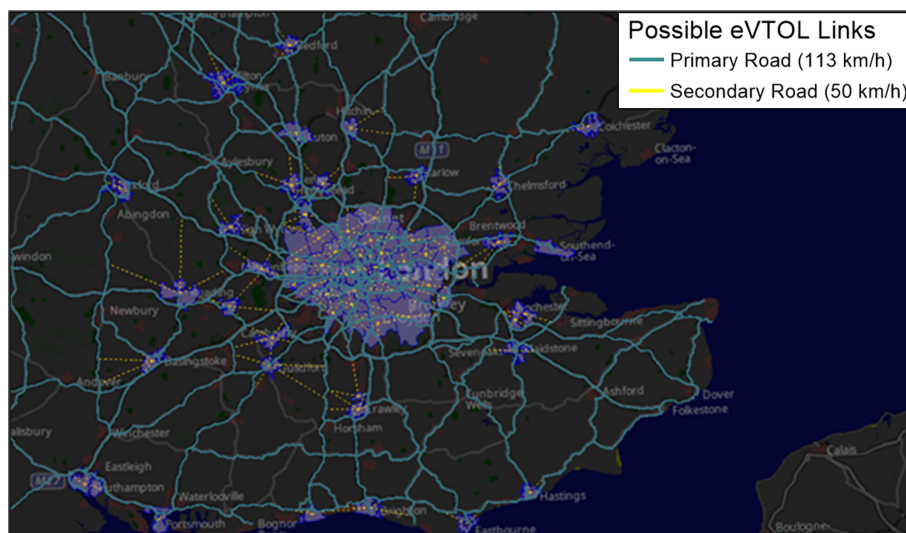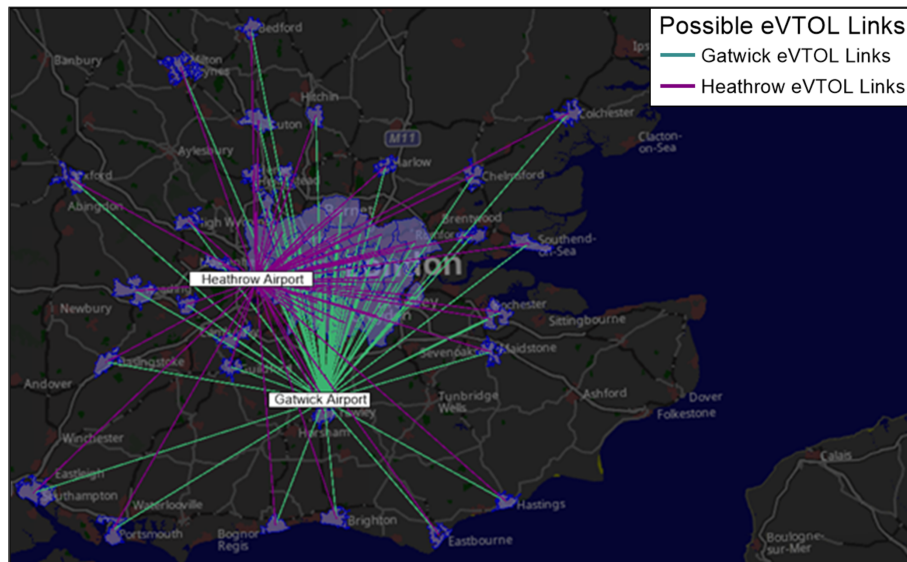

FIGURE 12: South East England simplified road network

1   The final model parameters consist of vehicle flight parameters, vertiport operational pa-
2   rameters, and vertiport investment costs. These are shown in Table 3.

FIGURE 13: South East England potential eVTOL routes

TABLE 2: Resulting airport-purposed utility function parameters for each person group

Mode	Person Group	ASC	β^{TC}	β^{TT}
Taxi	BHUK	0	-0.1323	-0.037
	BHUK			-0.067
	LMUK			-0.029
	LHUK			-0.039
	BMF			-0.048
	BHF			-0.087
	LMF			-0.038
	LHF			-0.050
eVTOL	BHUK	-0.4671	-0.1323	-0.033
	BHUK			-0.060
	LMUK			-0.026
	LHUK			-0.034
	BMF			-0.043
	BHF			-0.078
	LMF			-0.033
	LHF			-0.045

TABLE 3: Model parameters

Parameter	Value			Source
	Vehicle Parameters			
GS* [pers]	1.6295			(23)
T_{max} [h]	8			(23)
r_{ins} [-]	0.03			-
r_{CO2} [kg/MJ]	0.0786			(6)
r_{me} [[£/h]	79			(6)
r_{EC} [£/MJ]	0.0349			UK Standard
r_{ct} [£/kg]	0.014			UK Standard
r_{bat} [£/kWh]	130.5			(21)
S_{pilot} [\$]	100000			(21)
r_{ind} [-]	0.1			-
t [-]	0.19			UK Standard
Capacity	2			-
	Short Range	**Long Range**		
Range [km]	40	261		(18, 19)
Speed [km/h]	100	200		(18, 19)
VC [£]	176327	530962		(21)
C_{Bat} [MJ]	108	338		(18, 19)
SPL_{eVTOL} [dB]	75	77.9		(19, 32)
NDF [-]	1.23	1.50		-
r_{mt} [min/h]	30	60		(6)
Q_{cruise} [MJ/s]	0.057	0.083		(18)
$Q_{take-off}$ [MJ]	5.26	48.27		(18)
$Q_{landing}$ [MJ]	5.26	48.27		(18)
	Vertiport Parameters			
Number of Ports	5			-
VTOL frequency [/h]	30			-
VTOL clearance time [min]	2			-
Pad turnover time [min]	4			-
Boarding/Charging time [min]	6			-
eVTOL price factor [-]	1.7			-
Number of Pads**	1	≤ 6	> 6	-
$A_{land,pad}$ (m^2/pad)**	550	712	1300***	(33)
$C_{infra,pad}$ [£ million/pad]**	0.4	0.267	0.7	(33)
$C_{vertiport,pad}$ [£ million/pad]**	0.9	1.667	1.7	(33)

* Group size is taken as the average group size of both airports.
** The parameters show the values for vertipads, vertibase, and vertihubs respectively.
*** Land area separated based on two floors.

1 **Results Analysis**
2 The model presented in this paper is used to plan the optimal vertiport placement in South East
3 England considering airport-purpose trips. In the first instance, we determine the number of verti-
4 ports required, pricing scheme to use and eVTOL range. Once these parameters are specified, we
5 perform the optimisation of the network design that achieves the largest return of investment.

6 *Maximum Demand Coverage: Number of Vertiport Analysis*
7 In the first instance, we evaluate the improvement of the network catchment area for each addi-
8 tional vertiport added. As observed in Figure 14, the average daily demand capture per vertiport
9 decreases significantly for each new vertiport added, reaching a quasi-steady state after opening 20
10 vertiports. The reason for this trend is twofold: the best vertiports locations are allocated first, and
11 the increasing catchment overlap as more vertiports are added to the network.
12   Comparing long and short range services, demand capture increases at a faster rate for
13 short range vehicles due to demand zones being more agglomerated, especially in Greater London.
14 Nevertheless, for both ranges it can be determined that a reasonable range would be to open up
15 to ten vertiports. Note that for short range eVTOL, Gatwick and Heathrow airports are no longer
16 reachable via direct flight from every zone, reducing potential eVTOL demand substantially.

(a) Ratio of demand capture to maximum capturable
(Long Range)

(b) Ratio of demand capture to maximum capturable
(Short Range)

(c) Average demand per vertiport (Long Range)

(d) Average demand per vertiport (Short Range)
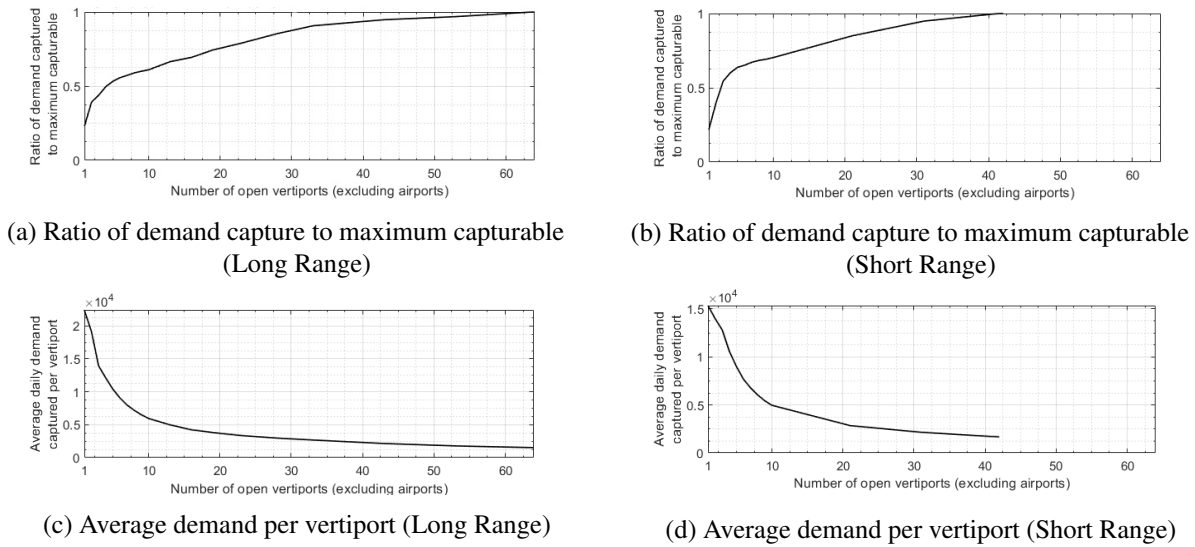
FIGURE 14: Variation of demand coverage (top) and the average demand per vertiport (bottom) based on
the number of open vertiports.

17 *Pricing Factor Analysis*
18 We analyse the spatial variation of ROI by evaluating a single vertiport in isolation. This allows
19 the visualisation of the performance of each location in the network. Figure 15 shows the effect of
20 the price multiplier (PM) to a) ROI and b) load factor
21   Despite the higher demands in Wesstminster, Woking and Guilford at $PM < 1.5$, their
22 ROI is the lowest in that range. Conversely, $PM > 2$ also yield low ROI due to decreasing demand
23 levels. The optimal *PM* range resides 1.4 to 2.0, where three distinct groups were identified (shown
24 different colour) and spatially distributed in Figure 16.

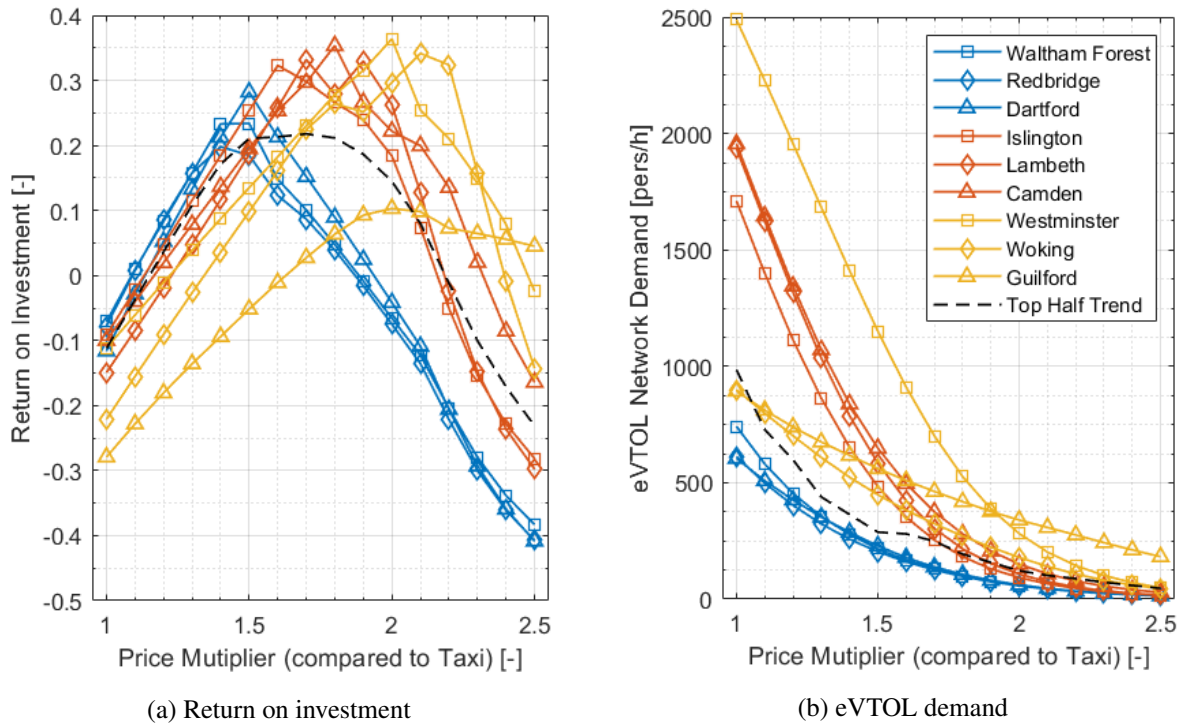(a) Return on investment   (b) eVTOL demand

FIGURE 15: Variation of optimal single city vertiports for each price multiplier (long range)

1   Lower PM yield the largest ROI for zones furthest from the airports (i.e. Dartford, Tower
2 Hamlets and Southampton). Note, however, that as per equations (49-50), trip price is proportional
3 to flight time, resulting in the highest trip prices of the network (see Figure 16. For this reason, the
4 ROI of this group decreases quickly for $PM > 1.5$.
5   Higher PM provides greater returns in London's central and high-income areas (Kensington
6 and Chelsea, Westminster and Woking). The remaining zones perform optimally with PM of 1.7-
7 1.8 (Lambeth, Islington, Camden).
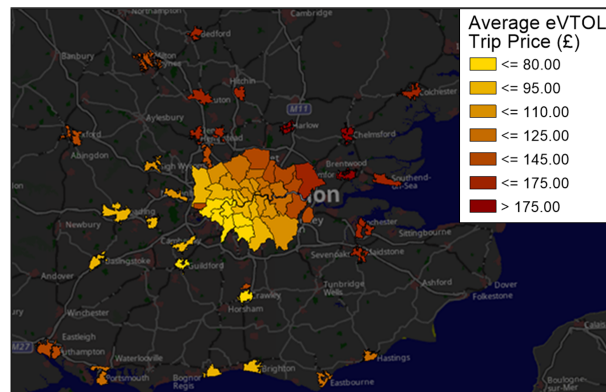
FIGURE 16: eVTOL average trip price spatial distribution.

8   The same experiment is carried using short range vehicle parameters as specified in Table
9 3. Figure 17 shows the variation of the ROI and total eVTOL demand with the PM of the best

1   performing zones. Note that, despite of the lower demands in short range vehicles, operational and
2   investment costs decrease due to the lower noise penalties and vehicle cost. As with the long range
3   case, three distinct groups are observed.

(a) Return on investment   (b) eVTOL demand
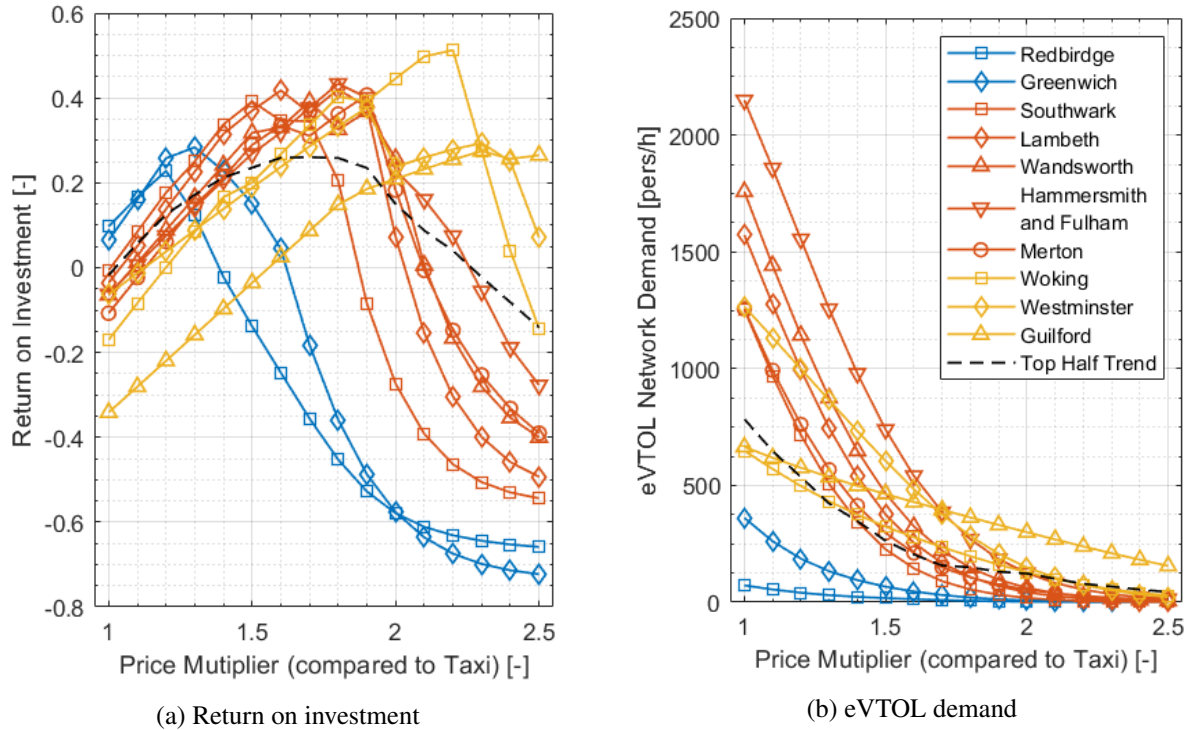
FIGURE 17: Variation of optimal single city vertiports for each price multiplier (short range)

4   The first group contains the zones furthest from the airports and yield an optimal ROI
5   at *PM* < 1.4. The large depth of discharge as a result of the long flight distances increase the
6   operational costs substantially as per equations (21-23), resulting in low land value requirements
7   to ensure a positive ROI.
8   The second group contain optimal ROI within *PM* ranges of 1.5 and 2.0 (Hammersmith and
9   Fulham, Wandworth, and Lambeth, among others). These zones are generally closely connected
10 to an airport and have a high population, with high demand being required to ensure profitability.
11   The final group is composed of regions with a large proportion of high-income customers
12 and very close proximity to the airports (Westminster, Woking and Guilford). The demand in these
13 areas are less affected by the *PM*, but seldom provide the highest ROI given the expensive cost of
14 land.

15 *UAM Network Analysis*
16 We analyse the the results of the algorithm under different passenger waiting times, seating capac-
17 ity and vehicle range (short and long). We also vary the pricing factor (1.4, 1.7, 2) and number of
18 vertiports (5, 10) based on the results of the previous sections.
19   The waiting time was chosen to be either 2 or 5 minutes. Finally, passenger seating capac-
20 ity was either 2 or 7, the first acting as private transport while the second as public transport as
21 proposed (*19*).

1   The resulting ROI are shown in Figure 18. For simplicity, we introduce the following
2 notation:

3                                    $R_{SC,WT}$

4   where R is the vehicle range type either Long Range (LR) or Short Range (SR), SC is the
5 seating capacity either 2 or 7, and WT is the waiting time either 2 or 5. For example, $SR_{2,5}$ denotes
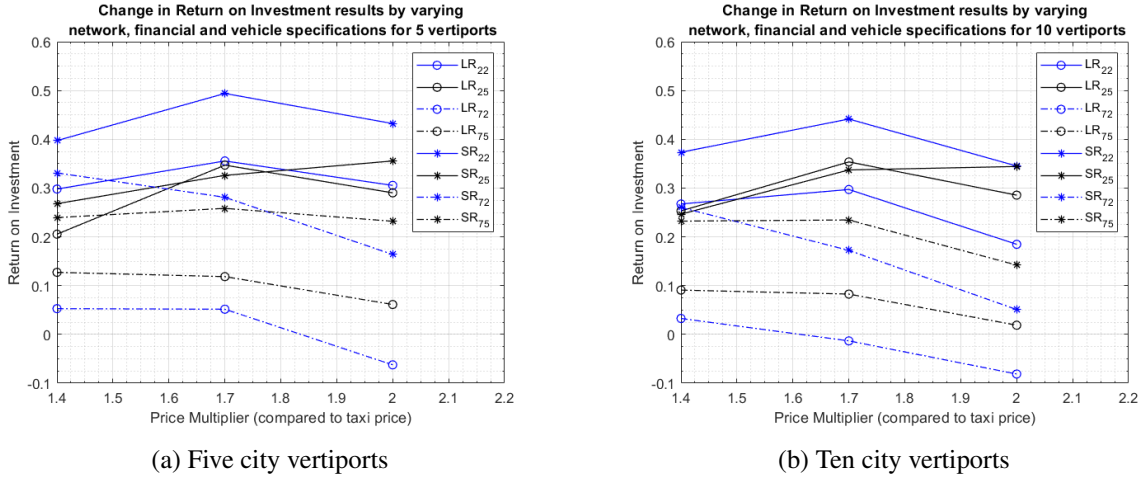6 the instance with short range vehicles, seating capacity of 2 passengers and 5 minute waiting time.

(a) Five city vertiports   (b) Ten city vertiports

FIGURE 18: Variation in ROI results based on the variable model specifications.

7   Results suggest that smaller capacity vehicles provide greater ROI overall, only $SR_{7,2}$ yields
8 higher ROI than $SR_{2,2}$ and $SR_{2,5}$ at $PM = 1.4$. The smaller vehicle size results in lower vertiport in-
9 frastructure costs, land requirements and noise disturbance requirements. The best ROI is obtained
10 at $PM = 1.7$ for $SR_{2,2}$, which coincides with the optimal range obtained in Figure 17.
11   Any increment in waiting times also results in a reduction in ROI, with the only exception
12 occurring when using ten vertiports at $PM = 2.0$, for $SR_{2,2}$ and $SR_{2,5}$. Longer waiting times require
13 larger terminals to sustain demand and, most importantly, eVTOL travel times increase overall, so
14 a larger proportion of the demand is lost to taxis. This generally means that providing higher
15 waiting time allowance will result in reduced ROI. However, longer waiting times ensure vehicles
16 are used more commonly at capacity, so the profit obtained per flight is greater.
17   Long range vehicles return lower ROIs on average, and the best performing instance is
18 $LR_{2,2}$ in the five vertiport case, and $LR_{2,5}$ in the ten vertiport case. The main difference of long
19 range network compared to the short range is that higher capacity vehicles proide greater ROI in
20 most instances.

21 *Maximising Return on Investment using Vertiport Placement*
22 Following the network analysis described in the previous section, we carry out additional experi-
23 ments based on the five vertiport $SR_{2,2}$ case which yielded the largest ROI. The optimal network
24 configuration shown in Figure 19 achieved a final ROI of 49.4%. An overall market penetration of
25 9.1% was recorded, which rose to 20% for business-class high income groups (see Figure 20).
26   The five vertiport locations chosen were Hemel Hempstead, Barnet, Haringey, Woking and
27 Wandsworth. Wandsworth provides low land acquisition costs compared to its surrounding areas
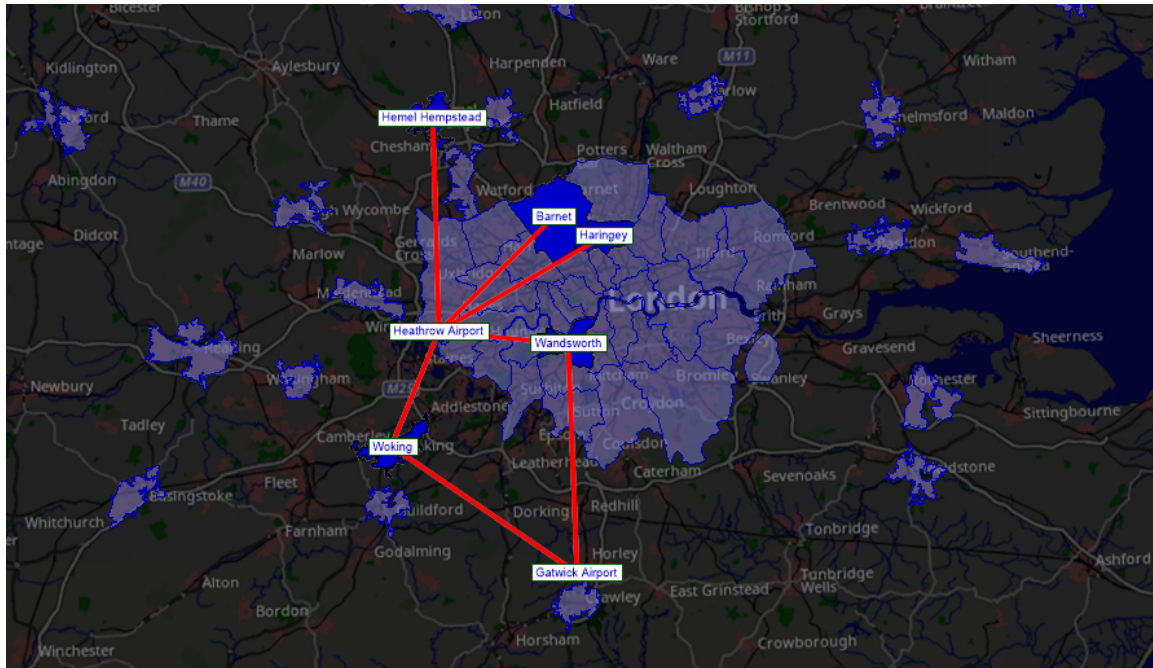
FIGURE 19: Optimal short range network (base specifications)

1 yet close proximity to high demand zones (Westminster, Kensington and Chelsea). In addition, it's
2 the only selected region that connects to both airports along with Woking.
3   Haringey and Barnet are neighbouring regions and provide greater catchment area in northen
4 Central London, which contains the largest proportion of high-income business trips. Finally, due
5 to their peripheral locations, Hemel Hempstead and Woking act as 'Park and Ride' stations for
6 trips from Greater London (see Figure 21). This means that travellers use the taxi mode outside
7 Greater London (where congestion is low) and then switch to the eVTOL in these stations to avoid
8 the city centre congestion.
9   This combination of central and peripheral vertiports allow travellers to bypass city centre
10 congestion, while also being located in regions with lower land value despite their proximity to
11 high-demand regions.
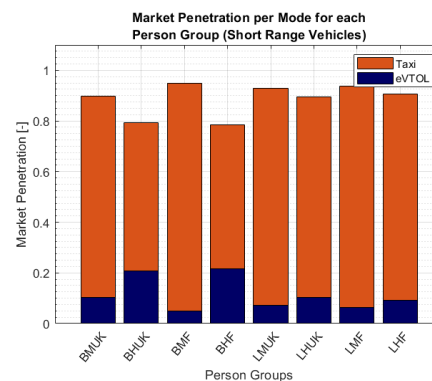
FIGURE 20: eVTOL Market Penetration for each person group
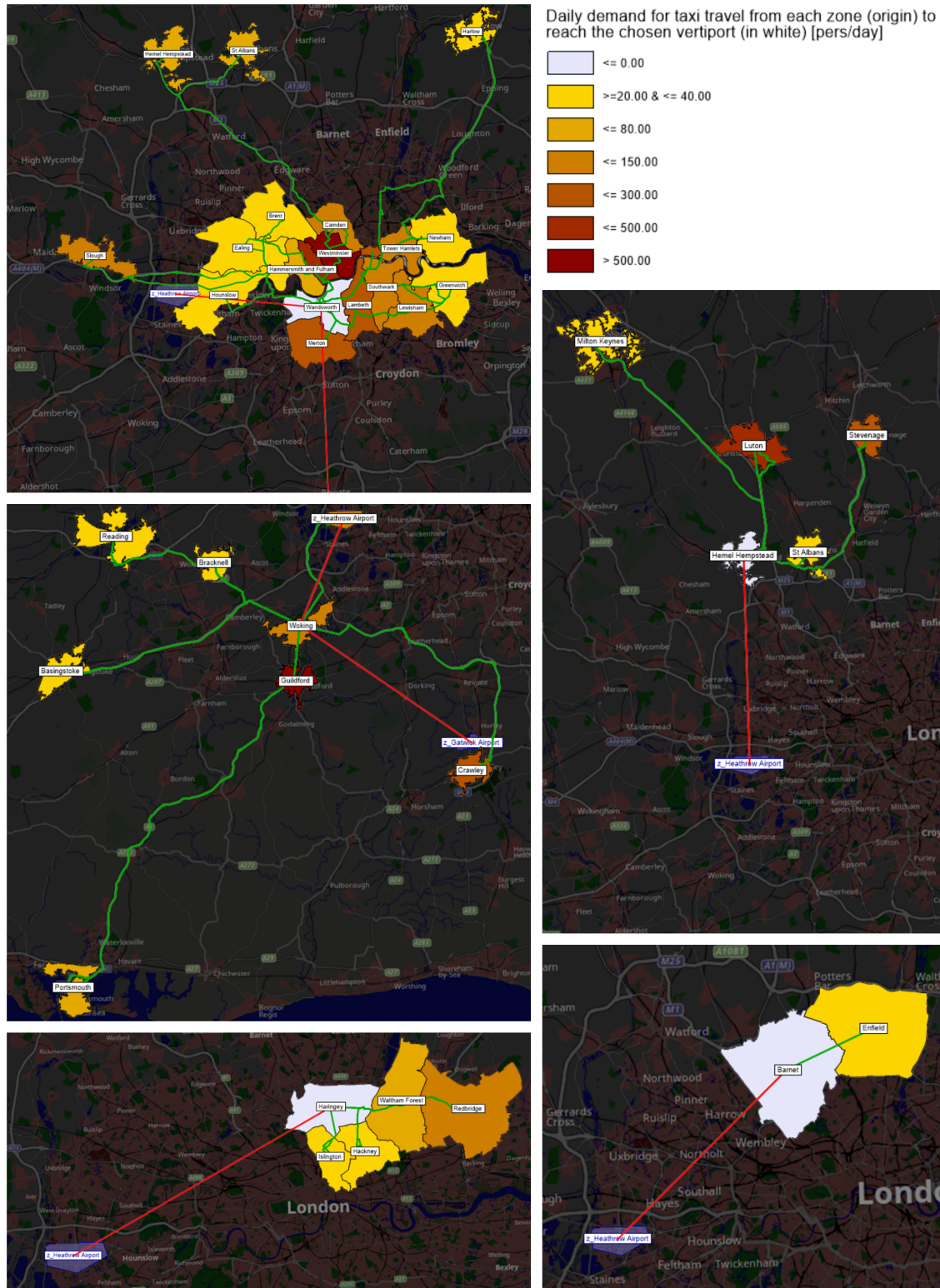
FIGURE 21: Attraction area (catchment) due to multimodality of each vertiport in the short range optimal network. From top to bottom: Wandsworth, Woking, Hemel Hempstead, Haringey and Barnet. Green links are taxi access trips, while red ones are eVTOL trips.

1   Table 4 summarises the revenue, operational and investment cost of each vertiport as well
2 their specifications. One can see that eVTOL ticket prices vary between £51.72 and £99.29 de-
3 pending on the proximity of the vertiport to the airport.

4   **TABLE 4**: Optimal network revenue, cost and operational requirements breakdown.

5

	Barnet	Haringey	Hemel Hempstead	Wandsworth	Woking	Gatwick	Heathrow	Total
Revenue								
Per Trip (Gatwick)[£]	-	-	-	90.06	88.94	13.60	-	-
Per Trip (Heathrow)[£]	85.64	99.29	84.19	69.61	51.72	-	17.85	-
Total [£ million/year]	10.79	9.68	12.45	49.23	44.66	54.72	74.81	256.34
Operational Cost								
Vehicle [£ million]	4.06	3.83	5.71	21.13	21.46	24.55	33.03	113.75
Vertiport [£ million]	1.96	1.67	2.3	9.82	10.16	9.7	17.07	52.68
Total [£ million]	6.02	5.50	8.01	30.95	31.62	34.25	50.10	166.43
Investment Cost								
Vehicle [£ million]	1.24	1.18	1.76	6.46	6.55	7.59	10.02	34.79
Vertiport [£ million]	0.31	0.27	0.37	4.05	4.18	3.99	7.03	20.2
Land [£ million]	7.75	7.04	5.91	25.2	12.95	9.02	24.61	92.44
Total [£ million]	9.30	8.48	7.99	35.71	23.69	20.60	41.66	147.43
Operational Parameters								
Demand (Gatwick) [pers/h]	0	0	0	95.87	113.60	-	-	209.47
Demand (Heathrow) [pers/h]	43.16	33.00	52.93	111.54	124.25	-	-	364.88
Passenger Pool (Gatwick)	-	-	-	2	2	-	-	-
Passenger Pool (Heathrow)	2	1.79	2	2	2	-	-	-
Travel Time (Gatwick) [min]	-	-	-	19.92	19.55	-	-	-
Travel Time (Heathrow) [min]	14.14	16.58	18.67	11.33	10.80	-	-	-
Number of Vehicles (Gatwick)	-	-	-	23	24	-	-	47
Number of Vehicles (Heathrow)	8	7	11	17	17	-	-	60
Total	8	7	11	40	41	47	60	214
Number of Pads	2	1	2	7	7	7	12	38

7   Finally, in terms of investment cost, Gatwick, Heathrow, Woking and Wandsworth are
8 considered vertihubs meaning the vertiports have two storeys, reducing the land area (and hence the
9 land cost share) but increasing its infrastructure cost. The resulting vertiport and vehicle investment
10 costs were significant mainly due to the high land cost in Greater London where most of the optimal
11 locations were found.

12 **DISCUSSION AND CONCLUDING REMARKS**
13 This paper has presented a holistic UAM network optimisation algorithm that incorporates mode
14 choice model in the demand for airport-purpose trips. To the best of the author's knowledge, it is
15 the first to simultaneously consider eVTOL demand modelling and network design to estimate the
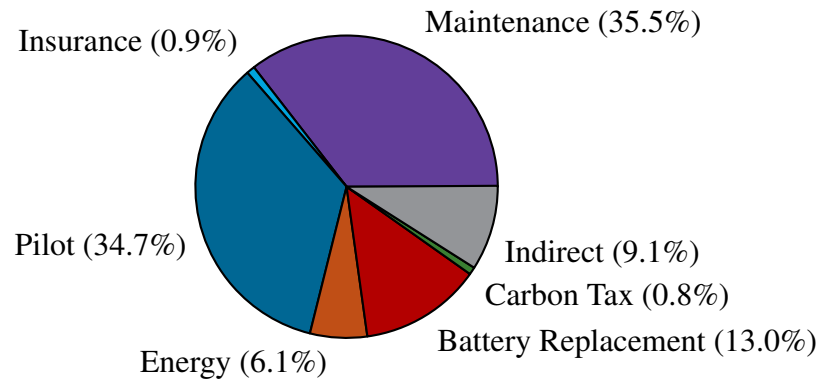
FIGURE 22: Vehicle operational cost breakdown,

1 financial viability of UAM. The model is applied to South-East England to facilitate airport access
2 the two main airports in the region: Heathrow and Gatwick.
3   The optimal UAM network defined by our algorithm structured proposed a set peripheral
4 vertiports acting as 'park and ride' stations and central vertiports in low land cost zones which are
5 in close proximity to high demand areas. This resulted in an ROI of 50%, similarly to that of HS2,
6 for a price multiplier of 1.7 compared to taxis (*34*).
7   Our analysis of the results revealed that higher return of investments were achieved for low
8 seating capacity, as larger capacities required greater operational costs and sufficiently high load
9 factors to provide a profit were not achieved. UAM operators should also seek to minimise waiting
10 times, as it reduces the vertiport size requirements.
11   The presented framework was the first to simultaneously consider eVTOL demand mod-
12 elling and both operating and investment cost. Additionally, being able to easily vary financial,
13 vehicle and network specifications has made the framework applicable to almost any urban area
14 with any number of airports, for different vehicle types
15   The framework developed in this paper provides a useful tool for governments to estimate
16 future traffic trends in the urban airspace, and calculate road congestion fluctuations caused by the
17 addition of vertiports in the city and its periphery. Studying these patterns can inform the develop-
18 ment of alternative and complementary public transport links to improve vertiport accessibility.
19   Industry organisations can utilise the models to design and evaluate UAM networks under
20 different constraints, and analyse whether an investment is beneficial in the long-term. The case
21 study presented shows it applicability to realistic case scenarios, and thus can be applied to other
22 regions provided sufficient data is available.
23   Note that only taxis were considered as the main competitor in this experiment. Improve-
24 ments in the public transport network and in particular the Elizabeth line and HS2 may result lower
25 market penetration and a reduced ROI. In addition, the eVTOL flight path were assumed to have no
26 obstacles. In practice, noise pollution requirements, no-fly zones, and other stochastic components
27 affect the final route plan, resulting in longer flight times and higher battery capacity requirements.
28   Furthermore, approximately 2,400 eVTOLs would take-off or land per day alone, which
29 coupled with the airport's current aircraft movement (1,300 take-offs or landings per day in the
30 case of Heathrow), will lead to significant pressure on ATC (*28*). A potential solution is the imple-
31 mentation of travel priority corridors to minimise interactions with aircrafts.

1 UAM operations were simplified assuming a constant headway, meaning congestion and
2 capacity restrictions were not fully considered. An agent-based simulation similar to (*6, 14*) would
3 provide a more realistic representation of vertiport operations, as well as the ability to consider
4 different passenger group sizes based on the passenger survey data.
5 Furthermore, the genetic algorithm used in the solution method means the final configura-
6 tion is not guaranteed to be optimal. However, given the problem complexity and size, an exact
7 solution method is infeasible. Nevertheless, further work should carried to develop heuristic that
8 accelerate solution convergence.
9 In summary, the findings of this study highlight the importance of multimodal modelling in
10 evaluating demand capture of vertiports. Indeed, the best performing zones in the case study have
11 generally prioritised cost reduction. By considering mutlimodality, passengers accessed vertiports
12 via taxi before using eVTOLs to the airport.
13 Nevertheless, the proposed approach can be further developed by performing an agent-
14 based simulation to include stochasticity in eVTOL trip requests. Additionally further research
15 can achieve more accurate utility functions and parameters estimation by using a detailed mode
16 preference survey able to provide a more realistic representation of airport travellers' behaviour.

17 **AUTHOR CONTRIBUTION STATEMENT**
18 The authors confirm contribution to the paper as follows: Serhal, Escribano Macias and Angeloudis
19 carried out the study conception and design, Serhal developed the models and analysed the results.
20 Escribano Macias and Serhal prepared the manuscript. All authors have reviewed the results and
21 approved the final version of the manuscript.

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