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Unified Framework for Scalable Vertiport Allocation with Heterogeneous Fleet Sizing: Case Study on the Republic of Ireland

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Advanced Air Mobility (AAM) is expected to transform urban and regional transportation. However, its successful deployment hinges on robust infrastructure planning that balances operational efficiency with scalable growth. Current vertiport allocation models typically deliver single, static network solutions without considering phased growth or aircraft performance limitations. This gap is addressed by presenting a unified framework that generates a scalable vertiport allocation plan in conjunction with system-performance-based heterogeneous fleet sizing. First, potential vertiport networks are generated through a distance-based agglomerative clustering algorithm applied to the census-based synthetically generated demand. Second, the mean vertiport network is established, and undergoes an elimination procedure aimed at maximizing passenger km travelled, to establish phased growth of the vertiport network. In order to determine the optimal development of the fleet as the network grows, the framework employs an agent-based simulation and conducts a parameter sweep across all combinations of vertiport network size, fleet size and fleet composition. This framework is validated on a use case on the Republic of Ireland. The results demonstrate the ability of the framework to deliver a demand-driven phased network introduction and expansion strategy, while identifying the optimal fleet size and composition at each growth stage. This approach provides stakeholders with a replicable foundation for capital allocation and regulatory planning in emerging AAM markets.

I. Nomenclature

C_{battery}	=	battery capacity
D	=	demand dataset
d_{ij}	=	distance vertiport i to j [km]
DoD	=	battery depth-of-discharge
E_{total}	=	total required mission energy
$\mathcal{F}$	=	phased fleet development plan
F	=	fleet configuration
MoE	=	measure of effectiveness
m	=	performance metric
N_f	=	fleet size
p_{ij}	=	number of passengers vertiport i to j
R_{mean}	=	mean inter-vertiport distance [km]
$R_{\text{net_mean}}$	=	commute-averaged distance [km]
R_{min}	=	minimum inter-vertiport distance [km]
s_i	=	incoming and outgoing commute distance served by vertiport i
T_{AAM}	=	total AAM trip time
T_{car}	=	car-equivalent trip time
$\mathcal{V}$	=	phased vertiport network allocation plan
V	=	vertiport network configuration

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v	=	vertiport
w	=	performance metric weight
η	=	heterogeneity factor

Subscripts

a	=	ED pair #
DS	=	demand served
EE	=	energy efficiency
i	=	vertiport #
LF	=	load factor
TS	=	time saved
x	=	commute #
y	=	scenario #

Superscripts

k	=	vertiport network configuration
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II. Introduction

The Advanced Air Mobility (AAM) sector is attracting major investment, with market analyses projecting a multi-billion dollar industry serving urban and regional markets within the next decade [1]. However, the path from technological demonstration to operational deployment remains uncertain. Unlike traditional aviation, which evolved over decades with established infrastructure and regulatory frameworks, AAM must be designed, certified, and deployed largely from scratch as a result of the inherent differences. Furthermore, the most significant capital requirements will not be carried by aircraft manufacturers, but by the operators and municipalities who have to build the vertiport networks that serve these systems [2]. Given that vertiports must be integrated into already dense urban environments and scaling the system could demand infrastructure upgrades, it could drive costs upward substantially or, if left unaddressed, could significantly constrain day-to-day operations if not accounted for in early stages of planning. This highlights a critical strategic aspect: the development of an AAM transportation system must be grounded in holistic data-driven planning methodologies that assess the phased development of the major faces of the system and accounts for the inherent interdependencies.

To this extent, Naeem et al. [3] have expanded on the work by Shiva Prakasha et al. [4] by developing a collaborative agent-based simulation, which incorporates an array of tools, namely, vehicle design, demand, mode choice, mission planning, vehicle allocation, vertidrome airside, trajectories and cost breakdown. Although they have booked significant headway, their analyses are constrained to homogeneous fleet(s), whereas the high variation in AAM trip distances may necessitate a heterogeneous fleet. Furthermore, rather than analytically deriving the vertiport locations, they are assumed [4].

Existing literature on vertiport location can be broadly categorized into four streams [5]: (1) location requirements and limitations [6, 7]; (2) geographic information system (GIS) studies correlating demographic and accessibility factors [8, 9]; (3) clustering-based algorithms that group demand points to identify candidate locations [10, 11]; and (4) optimization models that formalize location selection as a facility location or hub-location problem [12]. While each has merit, collectively they exhibit critical deficiencies:

- **Static Network Solutions:** Most approaches yield a single *optimal* network [5], ignoring the reality that AAM deployment will occur in phases, with network growth driven by market demand, capital availability, and regulatory approval. Jeong et al., Daskilewicz et al. [10, 13] have made progress in this respect by assessing multi-phase vertiport networks (10/20/40 vertiports and 40/100 vertiports respectively).
- **Inadequate Handling of Demand Uncertainty:** Few studies account for variability in demand patterns or test network robustness across multiple plausible demand scenarios.
- **Decoupling of Infrastructure and Operations:** Vertiport allocation is typically optimized independently of fleet characteristics, flight operations, and ground infrastructure constraints, despite these being inherently interdependent [11, 12, 14]. Shiva Prakasha et al., Escribano Macias et al. [4, 15] have begun to address this gap through integrated modelling.

This study covers the previous gaps by focussing on a framework that optimizes looks at demand, vertiport allocation, and fleet characteristics as a whole. Additionally, we recognize that vertiport allocation is not static: more vertiports may be added in the future. Therefore, the initial vertiport network should account for the potential inclusion of future vertiports. The following research question is thus posed: How can scalable, statistically robust vertiport networks that account for phased growth, demand variability, and operational constraints be designed, while optimizing the heterogeneous fleet required to serve them?

To answer these questions, the following objectives are established in this study.

- 1) Develop a synthetic demand generation methodology that creates statistically representative, multiple-scenario demand profiles for a region.
- 2) Formulate a scalable vertiport allocation algorithm that produces a family of network configurations reflecting progressive growth, rather than a single optimal solution.
- 3) Integrate vertiport network design with agent-based simulation to validate operational feasibility and assess system-level performance.
- 4) Establish a method for identifying optimal fleet sizing and composition as the network evolves.

To validate this framework, the AAM deployment for a national market, i.e. the Republic of Ireland, is used as the primary case study. The framework is designed to support initial infrastructure investment decisions and regulatory coordination.

This paper is organized as follows. Section III provides a comprehensive literature review, categorizing prior work and identifying methodological rationales. Section IV formalizes the technical problem. Section V details the methodology, decomposing the framework into demand generation, allocation, simulation, and performance analysis modules. Section VII describes the experimental setup for Ireland. Section VIII presents key findings. Section IX interprets these results in the context of AAM ecosystem challenges and stakeholder needs. Section X concludes with strategic implications.

III. Literature Review

This sections provides information on the state-of-the-art of the several components that build up the final framework: demand generator (subsection III.A), vertiport and network allocation (subsection III.B), eVTOL performance (subsection III.B), and fleet sizing (subsection III.B).

A. Demand Modelling and Synthetic Generation

Accurate demand estimation is fundamental to network planning. However, for an emerging market like AAM, real operational data does not yet exist, causing the need for demand projection methodologies. These range from:

- User Acceptance Willingness to Pay: predominantly through survey studies, assess the factors which affect the overall attitude towards AAM, as well as the users' willingness to use and pay [16–19].
- Mode Choice Models: Using stated or revealed preference data to estimate the likelihood that travellers will switch from ground or conventional modes to AAM [1, 20–22].
- Census-Based Aggregation: Identifying origin-destination pairs from commuting patterns in national censuses or travel surveys [13].
- Synthetic Generation: Creating multiple demand scenarios using Monte Carlo or similar methods to capture the variability and uncertainty inherent in preliminary forecasts.

EASA [16] has conducted an elaborate study on the societal acceptance of AAM in a number of European countries. The authors have found that 15% of people would be very likely to try out the AAM system for passenger transport purposes [16]. Haan et al. [21] used cell phone data and mode choice models to rank 40 U.S. cities by their potential for air taxi commuter services, identifying high-volume air taxi routes. Wei et al. [23] highlighted that air taxi demand is sensitive to access and egress times to vertiports, as well as aircraft range and operating costs. Daskilewicz et al. [13] used census data (LODES and American Community Survey) to estimate daily commuting patterns and aircraft range requirements for eVTOL daily commuting. For network planning purposes, synthetic generation is appealing because it allows for the creation of multiple, statistically equivalent demand scenarios, enabling robustness testing.

B. Vertiport Allocation and Network Design

The vertiport allocation problem has deep roots in operational research and regional planning. Traditional airport location studies balance factors like demographic demand, travel time, environmental constraints, and construction

feasibility. Vertiport allocation introduces new challenges because potential sites can include rooftops, parking lots, and dedicated pads. These sites may involve much smaller, lower-cost infrastructure compared to conventional airports [5, 12]. We focus primarily on three different approaches:

- **Clustering-Based Approaches:** K-means clustering and its variants have been widely adopted in UAM network planning. The strength of clustering lies in its relative simplicity and computational efficiency. Yet, traditional k-means does necessitate the analyst to pre-specify the number of clusters—a quantity usually unknown in early-stage network planning. This has stimulated an interest in adaptive clustering methods, encompassing both hierarchical and constrained techniques. Distance-based agglomerative clustering is another technique that derives the number of clusters from the data themselves via a distance threshold and as such minimizes analyst bias.
- **Hub Location Problems:** Some recent studies formulate vertiport placement as variants of the p-Hub Median Problem or the Uncapacitated Single Allocation Hub-Median Location Problem (USApHMP) [24]. The optimization frameworks are compatible with mixed-integer programming solvers and can include several objectives, such as demand coverage, travel time minimization, and cost minimization. Nevertheless, they usually produce a single "optimal" solution instead of a family of solutions appropriate for phased deployment and are computationally demanding for large networks [5, 25].
- **GIS-Based Suitability Analysis:** By combining demographic, geographic, environmental, and accessibility data, geographic information systems offer effective tools for multi-criteria evaluation of candidate sites [5, 26]. These techniques are especially useful for incorporating local constraints that may not be captured by mathematical models, such as zoning, noise restrictions, and existing infrastructure. GIS techniques, however, are frequently qualitative and might not adequately address demand uncertainty.

Despite their breadth, these approaches share a common weakness: they do not systematically model how vertiport networks should evolve to maximize demand. Most assume a static demand profile and optimize for a single network state. Furthermore, few models explicitly test whether the resulting network can achieve acceptable performance under operational constraints.

C. eVTOL Aircraft Design, Sizing and Performance Assessment

The performance effects of various architectures have been investigated in recent research on eVTOL aircraft design. A preliminary design framework for performance and noise assessment of UAM vehicles was presented by [27], which compared tilt-rotor and multicopter configurations. [28] looked at VTOL urban air mobility concept vehicles for technology development, emphasizing recurrent technological themes and performance goals that show up in candidate aircraft designs.

The two main architectural classes of eVTOL aircraft concepts under development are based on how lift is generated during cruise [29], and each has unique operational trade-offs:

- **Rotary-Wing Cruise (RWC):** These architectures, which include multi-rotors and compound helicopters, generate lift during cruise through rotor/propeller thrust. While mechanically simpler than fixed-wing architectures, they rely on powered lift rather than aerodynamic lift in all flight segments, making them less energy efficient during cruise. This severely limits range (typically 30–60 km) and cruise speed (100–150 km/h), making them suitable primarily for short urban hops [28, 30–32].
- **Fixed-Wing Cruise (FWC):** These architectures include lift+cruise, tilt-rotor, tilt-wing, and tilt-duct designs, and employ a fixed wing to generate lift during cruise. By decoupling vertical lift (from rotors during hover) from forward propulsion (from fixed-wing aerodynamics), these architectures achieve lower power requirements during cruise compared to RWC types. This results in significantly greater range (150–250 km) and higher cruise speeds (200–300 km/h).

eVTOL aircraft sizing is dominated by battery technology and must be performed iteratively over the segmented mission profile (hover, climb, cruise, descent) [33, 34]. The required battery capacity (C_{battery}) must satisfy the total mission energy (E_{total}) while accounting for a safe depth of discharge (DoD):

$$C_{\text{battery}} \geq \frac{E_{\text{total}}}{\text{DoD}} \quad (1)$$

FWC aircraft achieve higher cruise efficiency by exploiting fixed-wing lift-to-drag ratios of 8–15, whereas RWC aircraft benefit from large rotor areas and small disk loading in comparison [30]. Consequently, for a typical air taxi mission, the powered lift (FWC) type demonstrates mass efficiency when sized for missions above 10 km in range, while the simpler wingless (RWC) architecture is preferable for missions below 10 km in range, primarily due to better energy efficiency and simpler architecture [32]

System-of-Systems (SoS) studies demonstrate that aircraft sizing (e.g., cruise speed, battery capacity, payload) must be co-optimized with vertiport allocation, demand distribution, and fleet composition; treating aircraft design in isolation can lead to suboptimal network performance [31].

D. Fleet Sizing

Advanced Air Mobility is inherently a System of Systems, in which the aircraft, vertiport, airspace, and regulatory systems must be designed and operated coherently [4, 28, 31]. Shiva Prakasha et al. [4] developed a system-of-systems framework, which includes agent-based simulation (ABS) to model the complexities and interdependencies of the AAM system. ABS models individual agents (in this context, vertiports, aircraft or passengers), to interact dynamically within a shared environment. The data acquired through ABS may then be used to assess the performance of the system and accordingly, determine the optimal fleet size given the static vertiport network under consideration [31].

Although these studies provide valuable insights, they are constrained to the assessment of homogeneous fleets. Optimal network design may require a heterogeneous fleet containing RWC aircraft to serve short urban hops where low cost and mechanical simplicity are paramount, while FWC aircraft address longer regional connections where speed and range dominate [29]. Consequently, fleet composition represents a critical design variable. However, as the AAM network grows, the optimal fleet composition may evolve. Early stages with limited, high-density vertiport networks may favour one type, whereas later stages with dispersed networks may favour another. This suggests the need for a phased, correlated approach to fleet sizing and composition planning.

IV. Problem Formulation

In order to address the identified gaps, this section introduces how the problem is structured. We begin by outlining the key assumptions that frame how demand, aircraft, and infrastructure are treated in the study in subsection IV.A. The section continues with the mathematical problem statement in subsection IV.B.

A. Key Assumptions

The following assumptions are considered:

- 1) Vehicle Performance: Aircraft sizing and performance parameters are computed using the eVTOL aircraft sizing tool developed by Ratei et al. [29] and held fixed during the optimization. This is a simplification; ideally, aircraft requirements would be co-optimized with the network.
- 2) Passenger Choice: A trip is served by AAM only if the total AAM travel time (including ground access/egress and flight time) is less than or equal to the equivalent car-based trip time. Accordingly, it is assumed that trips with a straight-line distance smaller than $5km$ do not add value when choosing AAM as opposed to a car-based alternative. This binary choice model is more conservative than probabilistic choice models but is suitable for initial planning [21]. Furthermore, a trip may only be served by an aircraft if its range and overall performance characteristics allow it.
- 3) Vertiport throughput: All vertiports are identical in configuration — one take-off pad, two landing pads — reflecting a standardized, scalable design. They also have identical predefined operational constants (e.g. vertipad turnaround, taxi, boarding times) [35, 36]. Furthermore, it is assumed that all vertiports contain unlimited aircraft parking capacity. [28].
- 4) Safety Separation: A minimum separation is maintained between aircraft, modelled implicitly through vertipad turnaround time and a minimum inter-vertiport distance.
- 5) Air traffic management (ATM): The air traffic management (ATM) structure in this framework is simplified for initial modelling, assuming all aircraft operate at the same cruise altitude. This design choice, while suitable for preliminary analysis, potentially increases the risk of airborne conflicts, as real-world UAM operations demand unprecedented levels of traffic density and complexity [4, 28]. Consequently, the framework does not currently incorporate detailed ATM procedures or tactical conflict resolution mechanisms.

B. Mathematical Problem Statement

The objective is to determine a scalable vertiport allocation plan $\mathcal{V} = V^{k_1}, V^{k_2}, \dots, V^{\text{final}}$ and the corresponding optimal growth of the heterogeneous fleet $\mathcal{F} = F^{k_1}, F^{k_2}, \dots, F^{\text{final}}$, with $F^k = [N_f^*, \eta^*]^k$ that maximize system performance. Let:

- D = a demand dataset containing origin-destination pairs and departure times.
- V^k = vertiport network k , with k number of vertiports i.e. where $V^k = [v_1, v_2, \dots, v_k]$.
- v_i = vertiport i with coordinates $[\text{Lon}, \text{Lat}]_i$.
- N_f = the total number of aircraft in the fleet.
- η = the heterogeneity factor, defined as the ratio of multi-rotor aircraft to total fleet size: $\eta \in [0, 1]$.

For a given network configuration V^k , fleet size N_f , and composition η , the agent-based simulation produces a set of performance metrics $\mathbf{m} = m_1, m_2, \dots, m_p$, where each metric m_p and respective weight w_p quantifies an aspect of system performance. The performance metrics applied in this study are detailed in subsection V.E. The objective is to determine the combination (N_f^*, η^*) that maximizes a scalar Measure of Effectiveness (MoE) for each V^k under consideration, aggregating these metrics:

$$\text{MoE}(V^k, N_f^*, \eta^*) = \max [w_1 \cdot m_1(V^k, N_f, \eta) + w_2 \cdot m_2(V^k, N_f, \eta) + \dots + w_p \cdot m_p(V^k, N_f, \eta)] \quad (2)$$

subject to operational and infrastructure constraints (detailed in subsection IV.A). This is solved via parameter sweep and simulation. Although the optimal fleet size and composition are determined for each progressive stage of vertiport network growth, the transitional path and long-term strategy for fleet development must also be considered. While unexpected, abrupt shifts in network demand or operational requirements could theoretically lead to an uneconomical situation: the fleet composition optimized for one growth stage might favour the retirement or divestment of a specific aircraft type, only for that same type to become optimally required or strategically favoured again in a subsequent stage of network expansion. This non-linear evolution necessitates a phased, correlated approach to fleet sizing and composition planning, ensuring procurement decisions account for operational longevity and network adaptability rather than solely maximizing performance at an isolated stage.

V. Methodology

Building on the problem formulation, the integrated framework is operationalized through the workflow shown in Figure 1 and integrates five modules within a systems workflow:

- 1) Synthetic Demand Generator: Generates y number of statistically distinct commute datasets based on census data.
- 2) Scalable Vertiport Allocator: Generates y corresponding ‘final’ vertiport network configurations and identifies the statistically mean network. Filters commute data, ranks vertiports based on travelled commute distance, and eliminates vertiport until desired vertiport network sizes are acquired.
- 3) Aircraft Sizing and Performance Analysis: Determines aircraft sizing and performance parameters.
- 4) Agent-Based Simulation: Conducts agent based simulations for all combinations of vertiport network size, fleet size and fleet composition, and evaluates operational feasibility. The data generated after conducting operations is extracted.
- 5) System Performance assessment: Computes performance metrics based on the data extracted during ABS.

Each module addresses a key AAM facet, and together enable the evaluation of scalable AAM network configurations under phased stages of growth. These modules are presented sequentially in subsection V.A–V.E.

A. Module 1: Synthetic Demand Generation

The objective within this module is to generate y statistically representative commute datasets for Ireland that reflect variability in demand patterns. To do so, national census commute-to-work/school/college data for Ireland is obtained [37], providing home and work/school locations, as well as the total number of commutes to be generated per scenario (y). Although this translates into the same number of commutes generated for each scenario, variability is integrated in the randomizers applied in the following steps of the module. Origin-destination matrices are constructed at the electoral division (ED) level and the probabilities of commutes between all ED pairs are determined. Furthermore, geographic data containing the ED boundaries is obtained [38]. Since the geographic boundary definitions of the EDs may contain bodies of water and the vast majority of people reside on land, a dataset containing all bodies of water is acquired [39, 39] and subtracted from the original ED boundary dataset. As a result, longitude and latitude pairs for each OD pair may be generated. To determine the departure time of each commute, census departure-to-work/school/college data is gathered [40]. It contains the number of people departing to work within a range of time frames per ED. Consequently, the probabilities of people departing to work within each time frame may be determined for each ED. For each commute in each scenario (y), the commute details are determined by:

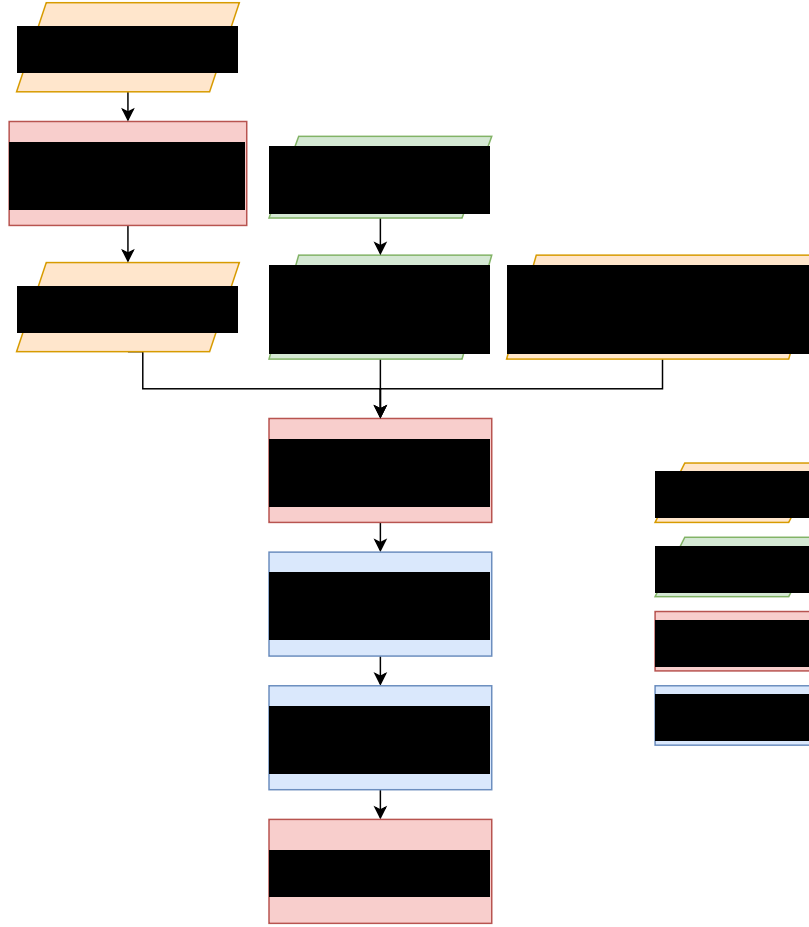


Fig. 1 Scalable vertiport allocation and heterogeneous fleet sizing workflow

- Sampling from the OD probability distributions to determine the origin and destination ED names.
- Sampling from the ED boundary data to determine the longitude and latitude for the origin and destination based on their respective electoral division.
- Sampling from the departure ED timeframe probabilities to generate the exact departure time.

The output of this module is y demand datasets, each containing x origin-destination pairs with assigned departure times.

B. Module 2: Scalable Vertiport Allocator:

Based on the y demand datasets established by the synthetic demand generator, the objective of the scalable vertiport allocator is to generate phased vertiport allocation plan. The workflow is presented in Figure 3. It may be split up into three main stages, namely 1) agglomerative clustering, 2) mean ‘final’ network V^{final} and 3) phased growth path.

Stage 1: Agglomerative clustering: For each demand dataset D_y , a distance-based agglomerative clustering algorithm is applied. To ensure that the vertiports are allocated based on viable trips alone, it starts with the application of a minimum trip distance filter (Filter 1). All commutes with a straight-line distance smaller than 5km are filtered out before agglomerative clustering, as the benefit of using AAM is assumed to be negligible compared to car-based alternative subsection IV.A. Each origin and destination of the OD pairs are treated as independent locations. To allow for large scale demand handling, initially a k -NN search is conducted with $k = 80$. This is followed by the development of a sparse symmetric adjacency matrix, which represents the connectivity matrix. The agglomerative clustering algorithm is initialized by providing the demand data, connectivity matrix, and initial distance threshold. The algorithm views the locations as individual clusters, which are progressively merged based on inter-cluster distance. This occurs globally unless the connectivity matrix contains multiple components, in which case clustering is applied

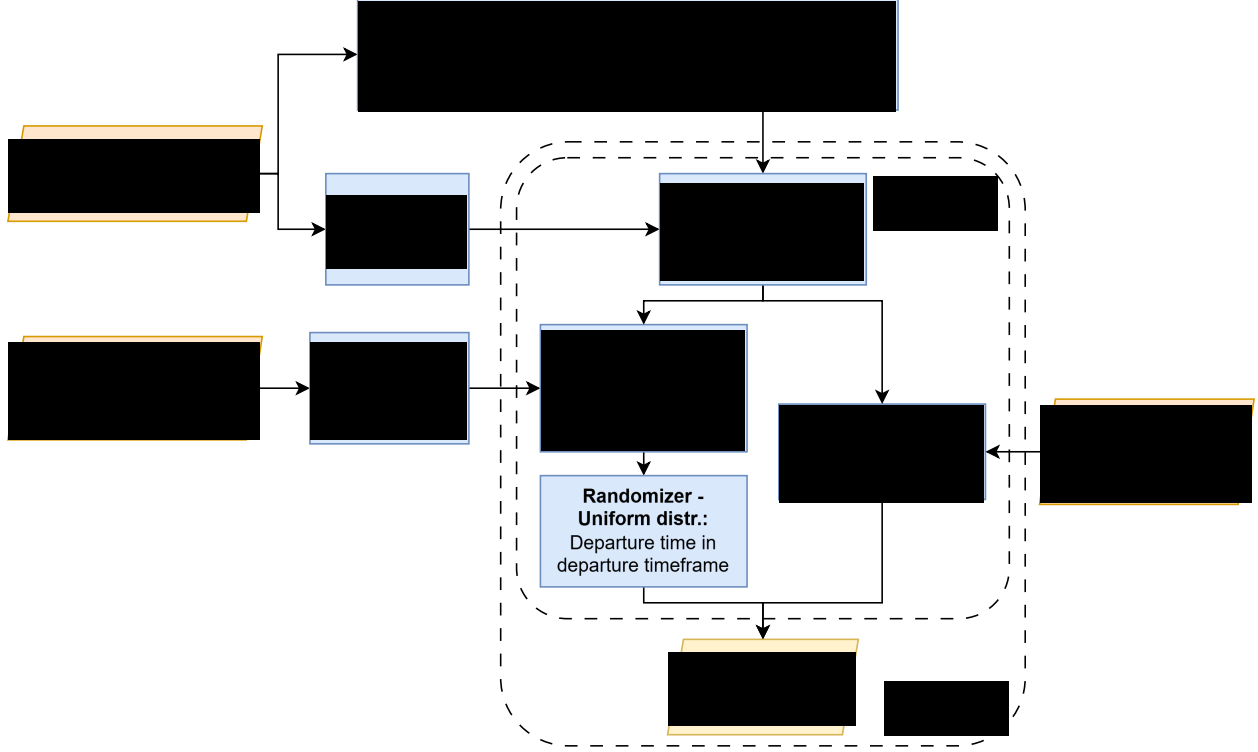


Fig. 2 Demand generator workflow

to each component separately. The algorithm terminates when the minimum inter-cluster distance falls within the 10 – 11 km range, yielding the "final" network size. In case a certain level of refinement of the distance threshold is achieved and the resulting minimum inter-cluster distance falls outside of the range, the algorithm is terminated and the clustering round fails. The output of this stage is a network configuration V_y^{final} for each demand dataset D_y , containing the optimal number of vertiports and their locations.

Stage 2: Mean ‘final’ network: The vertiports across the successful ‘final’ vertiport networks (V_y^{final}) are grouped using an iterative greedy radius-bounded clustering algorithm, with a radius of 5 km such that overlapping of clusters is minimized. The mean vertiport longitudes and latitudes are then determined using $[\text{Lon}, \text{Lat}]_{i_{\text{mean}}}^{\text{final}_y} = \text{mean}([\text{Lon}, \text{Lat}]_i^{\text{succes}_y}, [\text{Lon}, \text{Lat}]_i^{\text{succes}_{y+1}}, \dots)$, where i represents the cluster number and y represents the cluster entry origination from the y^{th} successful agglomerative clustering scenario. The mean vertiport locations form the ‘final’ vertiport network, $V_{\text{mean}}^{\text{final}}$, used in the remainder of the workflow i.e.. V^{final} . The standard deviation within clusters is also determined, using $[\text{Lon}, \text{Lat}]_{i_{\text{std}}}^{\text{final}} = \text{std}([\text{Lon}, \text{Lat}]_i^{\text{succes}_y}, [\text{Lon}, \text{Lat}]_i^{\text{succes}_{y+1}}, \dots)$, where i represents the cluster number and y represents the cluster entry origination from the y^{th} successful agglomerative clustering scenario. The output of this stage is the mean ‘final’ vertiport network ($V_{\text{mean}}^{\text{final}} = V^{\text{final}}$). Furthermore, the scenario whose vertiport network is closest to the mean network is identified and the corresponding demand is selected for the remainder of the workflow (D^{final}).

Stage 3: Phased growth path: To represent phased network growth, a commute-distance-based elimination procedure is applied to the mean ‘final’ network (V^{final}). To model user acceptance, the remaining commutes (i.e., after application of filter 1 to the best matching commute dataset, D^{final}) are randomly sampled such that 15% chooses AAM (very likely to try out passenger transportation form of AAM [16]) and the remainder choosing an alternative transportation method. The allocator continues by scoring each vertiport (v_i) in V^{final} based on the total incoming and outgoing commute kilometers directly served: $s_i = \sum_j (d_{ij} \cdot p_{ij} + d_{ji} \cdot p_{ji})$, where d_{ij} is the distance from vertiport i to vertiport j , and p_{ij} is the number of passengers travelling from i to j . The lowest-scoring vertiport is removed, and remaining demand is redistributed to the nearest available vertiport using a k-dimensional (k-d) tree algorithm for efficient nearest-neighbour search. Filters:

- Pre- and post AAM trip - Filter 3: A maximum pre- and post AAM trip distance of 50 km is accepted to ensure

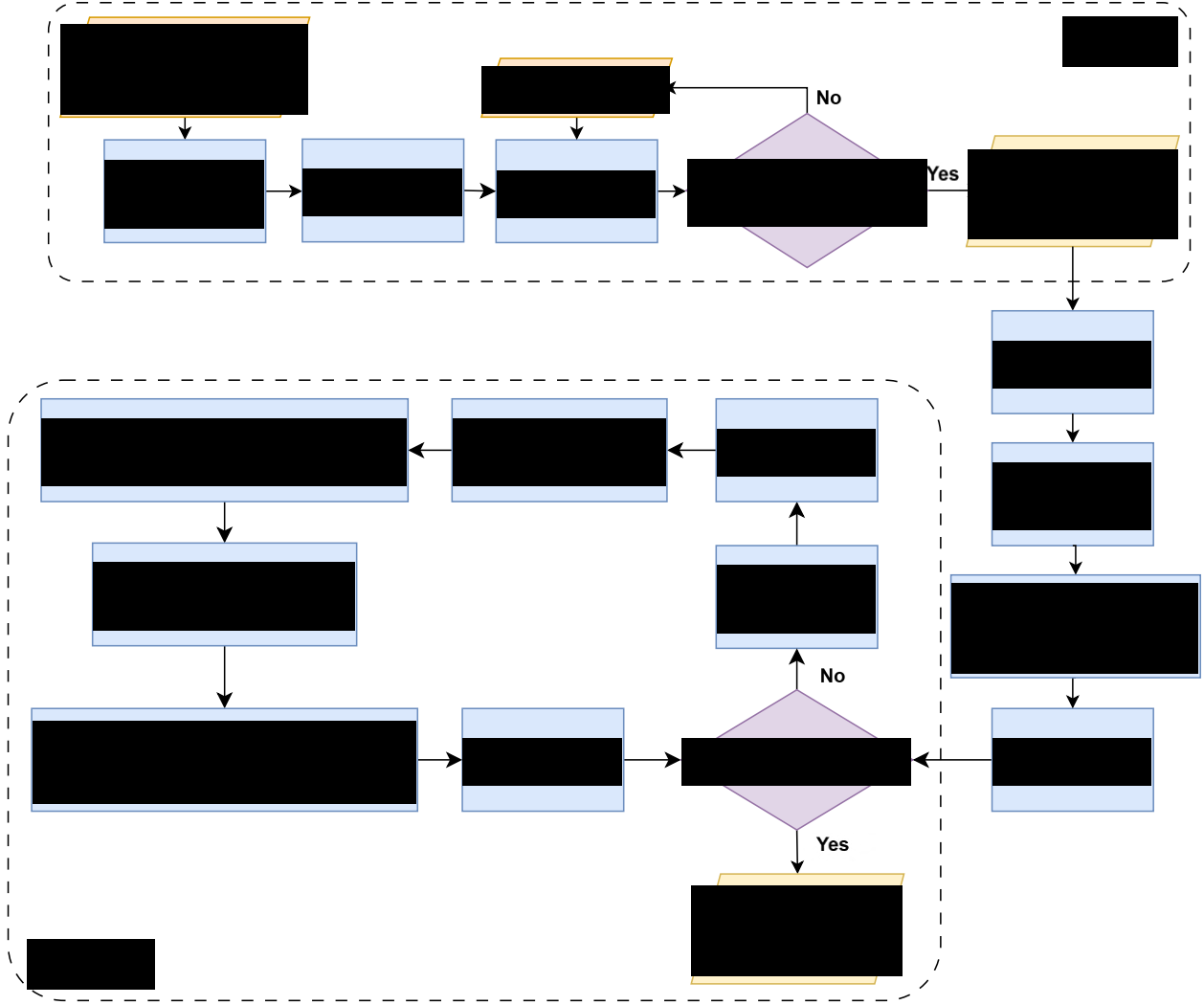


Fig. 3 Scalable vertiport allocator workflow

that solely trips with locations in the rough vicinity of vertiports are accounted for.

- Trip comparison - Filter 4: Trips with a total AAM trip time longer than a car-based alternative trip time are filtered out. The same is applied to the trip distance.
- Operational window & Simulation time frame - Filter 5: To account for noise, the operational window is set to 8:00 - 20:00. However, the study only assesses morning commute-to-work trips, thereby constraining the ultimate simulation window to 8:00 - 12:00.
- Non-identical Vertiports - Filter 6: It may occur that both locations of an OD pair are directed to the same vertiport. In this case, the trip is filtered out.

The remaining vertiports are rescored after and is followed by the next elimination round. The removal process iterates until all desired network sizes are defined, producing a phased vertiport allocation plan: $V^{k_1}, V^{k_2}, \dots, V^{\text{final}}$. Consequently, the output of this module is a scalable vertiport network ($\mathcal{F}$) derived from the representative demand dataset, representing growth stages from an initial small network up to the full final network V^{final} . Furthermore, corresponding filtered commute datasets (D^k up to D^{final}) are extracted for the agent-based simulation.

C. Module 3: Aircraft Sizing and Performance

The objective of this module is to define aircraft performance parameters for two eVTOL types (multi-rotor and tilt-rotor) to be used in the agent-based simulation. Representative multi-rotor and tilt-rotor concepts are defined,

incorporating current industry understanding of [27, 31]:

- Mission profile.
- Cruise speed.
- Range for payload.
- Turnaround time.
- Specific energy and power.
- Charge rate.

Using the eVTOL aircraft sizing tool developed by Ratei et al. [29], the sizing and performance characteristics are established. The output of this module is two sets of aircraft performance parameters used as inputs to the simulation.

D. Module 4: Agent-Based Simulation

This works used the agent based simulation tool developed by Shiva Prakasha et al. [4]. It performs simulations within a given time-frame and gathers the data for the performance assessment to follow. A parameter sweep is conducted across network configurations (V^k), fleet size (N_f) and fleet composition (η), and the operational data of each combination is collected. It does so in two stages, namely 1) simulation setup and 2) operational simulation.

Stage 1: Simulation setup: For a given network configuration V^k , fleet size N_f , and composition η , each vertiport is configured with 1 take-off pad and 2 landing pads. The number of parking spaces is unlimited. $N_f \cdot \eta$ multi-rotor aircraft and $N_f \cdot (1 - \eta)$ tilt-rotor aircraft are positioned and assigned to initial vertiports. The filtered demand from the representative dataset is injected into the simulation over the course of a simulated morning (8:00 to 12:00).

Stage 2: Operational simulation: The simulation operates at a high level of abstraction. Each morning commute trip (OD pair with departure time) is submitted as a request. A request is assigned to an aircraft based on range and timing. If no aircraft is available, the request is queued. If not at the origin vertiport already, the aircraft transits from its current vertiport to the origin vertiport, picks up passengers, flies to the destination, and deposits passengers. Each trip consumes time and energy according to the covered distance, number of passengers and aircraft type. After delivery, the aircraft returns to a charging. Aircraft take-off and land as soon as an appropriate vertipad is available. In case a landing vertipad is not available upon request, the aircraft is placed in a holding pattern and the request is queued. The same holds for take-off operations. The simulations are conducted and the data required for the system performance assessment is gathered.

The outputs of this module include:

- Served Demand: The total number of AAM trips successfully completed.
- Unserved Demand: Trips that could not be served due to lack of available aircraft, vertiport congestion, or range limitations.
- Energy Consumption: Total battery energy drawn by all aircraft.
- Load Factor: Average passengers per completed flight.
- Trip Times: For each completed trip, the total time from request submission to arrival at destination.
- Passenger Wait Times: Time spent queuing at vertiports due to unavailable aircraft or pads.

E. Module 5: System Performance Analysis

The objective of this module is to determine the overall system performance based on the operational data gathered through the agent based simulation and identify the optimal fleet size and composition throughout phased growth of vertiport network. The framework assesses system performance across four key dimensions, drawing from AAM planning studies [15, 31]:

- 1) Demand Served (DS): The filtered demand that is actually served by the AAM system. Aims to maximize market penetration:

$$m_{DS} = \frac{\text{converted requests}_i(\text{fleet size, heterogeneity factor}) - \text{converted requests}_{i_{min}}}{\text{converted requests}_{i_{max}} - \text{converted requests}_{i_{min}}}, \quad (3)$$

where m_{DS} refers to the metric of demand served.

- 2) Energy Efficiency (EE): The total energy consumed by the fleet. Aims to minimize energy consumption, thereby decreasing operating costs.

$$m_{EE} = 1 - \frac{\text{fleet energy}_i(\text{fleet size, heterogeneity factor}) - \text{fleet energy}_{i_{min}}}{\text{fleet energy}_{i_{max}} - \text{fleet energy}_{i_{min}}}, \quad (4)$$

where m_{DS} refers to the metric of the energy efficiency.

- 3) Load Factor (LF): The average number of passengers per flight as a fraction of aircraft capacity. This metric aims to maximize asset utilization:

$$m_{LF} = \frac{\text{average load factor}_i(\text{fleet size, heterogeneity factor}) - \text{average load factor}_{i_{min}}}{\text{average load factor}_{i_{max}} - \text{average load factor}_{i_{min}}}, \quad (5)$$

where m_{DS} refers to the metric of load factor.

- 4) Time Savings (TS): The average time saved per trip compared its car-based equivalent. This metric aims to maximize core value proposition to passengers.

$$m_{TS} = \frac{\text{average time saved}_i(\text{fleet size, heterogeneity factor}) - \text{average time saved}_{i_{min}}}{\text{average time saved}_{i_{max}} - \text{average time saved}_{i_{min}}}, \quad (6)$$

where m_{TS} refers to the metric of time savings.

As defined in subsection IV.B, these performance metrics are combined and respective weights are added to form the Measure of Effectiveness (MoE):

$$\text{MoE} = w_{DS} \cdot m_{DS} + w_{EE} \cdot m_{EE} + w_{LF} \cdot m_{LF} + w_{TS} \cdot m_{TS}, \quad (7)$$

where:

- $w_{DS} = 0.4$
- $w_{EE} = 0.3$
- $w_{LF} = 0.1$
- $w_{TS} = 0.2$

The weights may vary based on stakeholder priorities (revenue potential, environmental responsibility, cost control, customer satisfaction) and may be assigned accordingly. The MoE is calculated for every combination of vertiport network (V^k), fleet size (N_f) and fleet composition (η). The output of this module is the Measure of Effectiveness, $\text{MoE}(V^k, N_f, \eta)$, for each combination in the parameter sweep tested. Based on the MoE, the optimal fleet growth path is established.

VI. Use Case

This section defines the use case compiled to test the validity of the framework and provide proof of concept. It starts with the definition of the case study (i.e. location) in subsection VI.A and continues by establishing the considered demand profile in subsection VI.B.

A. Case Study: Republic of Ireland

The framework is applied to a comprehensive case study for the Republic of Ireland, a country with a population of ~5.5 million [41] and a surface area of ~70,000 km². It has a dispersed population with concentration in Dublin, Cork and Galway as observable in Figure 4. This is suitable for exploring both dense urban and lower-density regional networks. It also has good access to the required national census data as defined in subsection V.A, via the Irish Central Statistics Office [37].

B. Demand Profile

The number of demand generation scenarios is set to 50. The generated trips are constrained to commute-to-work/school/college [37], representing peak demand. Although the ranges of time-frames in [40] span from 00:00 to 17:31, the time window simulated in the ABS is constrained to 8:00 to 12:00. This is done to capture a part of the peak demand, which is expected to occur from 06:30-09:30, and combined with the operational window of 8:00-20:00 to account for the annoyance factor of the noise generated by the eVTOL aircraft. Furthermore, as defined in subsection V.B, only trips with a straight-line distance longer than 5 km are considered viable for AAM; shorter trips are better served by ground transport. Finally, a trip is marked as "AAM-competitive" if $T_{AAM} < T_{Car}$, where T_{AAM} includes flight time plus ground access/egress and T_{Car} is derived from a travel time model based on distance and typical road speeds.

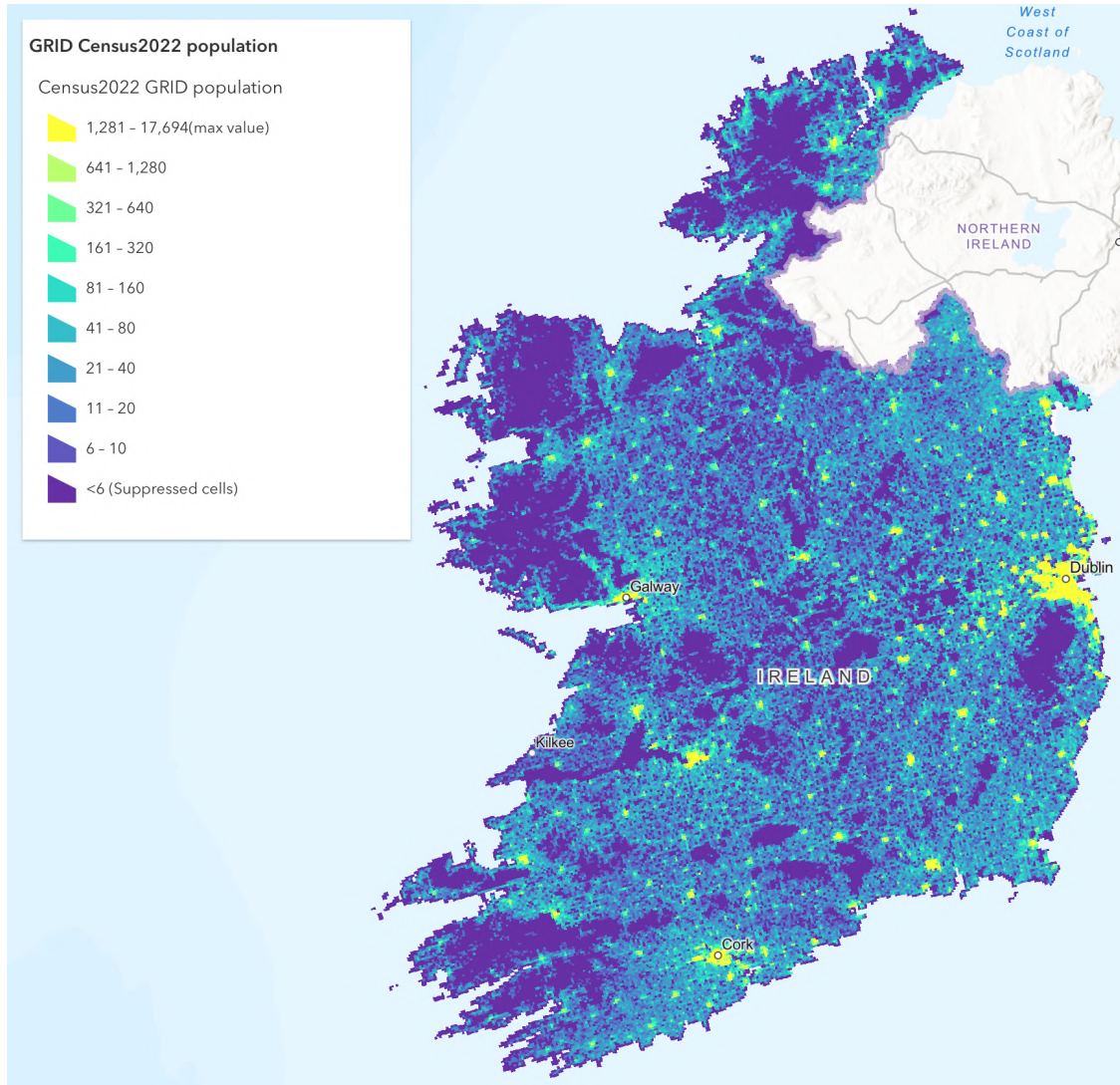


Fig. 4 Population density Ireland, per km² [42].

VII. Experimental Setup

Following the definition of the use case, this section details the experimental setup adopted in this study. Subsection VII.A contains the aircraft sizing metrics used to establish the aircraft which serve the transportation system. It also contains the relevant details on the vertiport configuration modelled in the ABS. This section ends with the parameter sweep conducted to determine the optimal phased growth path of the fleet in subsection VII.B.

A. Aircraft and Vertiport Configuration

The eVTOL aircraft modelled in this paper have been done so according to the parameters presented in Table 4. Furthermore, all vertiports modelled in the study contain a single take-off pad and two landing pads. At this stage, all vertiports have unlimited parking capacity, and no direct limit on passenger throughput is imposed. Future work may improve upon this by integrating a dynamic pad and capacity allocation algorithm, which allows for observation of the evolution of vertiport capacity requirements. Vertiport throughput limitations have been modelled through a (take-off and landing) vertipad turnaround time of 15 s. This constrains the number of landing and take-off procedures to 240/hour per vertipad. This indirectly also limits the passenger throughput. After the landing procedure has concluded, the aircraft taxi-in for 120 s, after which passenger de-boarding takes 90s. For take-off, the procedure starts with a boarding time of 90 s, followed by a taxi-out time of 120 s, and finally take-off procedure of 15 s. In case a take-off or

landing vertipad is not available, the procedure is queued.

Table 4 Design parameters used to size the multi-rotor and tilt-rotor aircraft.

	Design variable	Multi-rotor	Tilt-rotor	Unit
Design	Persons on board (incl. 1 pilot)	3	4	pax
	Payload mass	270.0	450.0	kg
	Cruise speed	35.0	65.0	m/s
	Range	50.0	200.0	km
	Maximum disk loading	750.0	750.0	N/m ²
	Powertrain efficiency	0.9	0.9	-
	Propeller efficiency	0.8	0.8	-
	Number of rotors	18	6	rotors
	Battery specific energy	300.0	300.0	Wh/kg
	Battery specific power	2.0	2.0	kW/kg
Mission related	Altitude - Vertiport	0.0	0.0	m
	Altitude - Vertical climb	15.2	15.2	m
	Altitude - Cruise	457.2	457.2	m
	Reserve time.	30.0	30.0	min
	Transition time	35.7	71.4	s
	Vertical climb and descent rate	0.5	0.5	m/s
	Cruise climb and descent rate	3.6	3.6	m/s
	Passenger carrying flight	Piloted	Piloted	-
	Deadhead flight	Autonomous	Autonomous	-
	Battery swap enabled	False	False	-
	Charge rate	2C	2C	-

B. Parameter Sweep

For each network size (representing growth stages) simulated in the ABS, a comprehensive parameter sweep is conducted. For the purpose of presenting the proof of concept, the simulations cover a limited segment of network growth. The network configurations along with the variations in fleet size and composition are provided in Table 5. k in the vertiport networks refers to the number of vertiports in the respective network configurations. This sweep systematically explores the design space, identifying optimal fleet composition patterns as the network evolves. Although the range of vertiport network configurations assessed in the parameter sweep does not cover all phases of growth, it aims to provide a proof of concept.

Table 5 Parameter sweep variables

Variable	Value
Vertiport network, V^k	V^5, V^{10}, V^{15}
Fleet size, N_f [aircraft]	25, 50, 75, ..., 975, 1000
Heterogeneity factor, η	0.00, 0.05, 0.10, ..., 0.95, 1.00

VIII. Results

This section presents the results of the use case and experimental setup as defined in section VI and section VII, respectively. First, the results of the synthetic demand generator are provided in subsection VIII.A. Second, the vertiport network and its phased development is established in subsection VIII.B. Third, the performance characteristics of both eVTOL aircraft are presented in subsection VIII.C. Finally, the results of the phased fleet development plan can be found in subsection VIII.D.

A. Synthetic Demand

The synthetic demand generated for scenario 0, presented in Figure 5, confirms the expected demand concentration of the synthetic commute dataset generated for Republic of Ireland use case (output of module 1, detailed in Figure 2). This visualization aligns with that of the population density provided in Figure 4; concentrations of origin and destination locations can be observed in Dublin, Cork and Galway. Furthermore, this confirms the presence of a spectrum of trip lengths, indicating a market for Urban Air Mobility (UAM) as well as Regional Air Mobility (RAM).

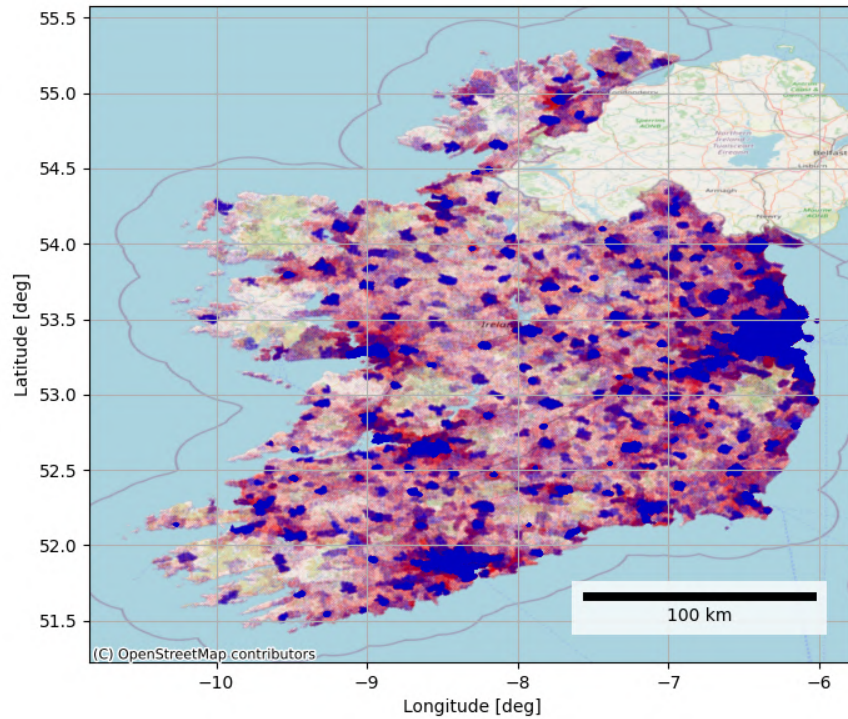


Fig. 5 Synthetic demand generated for the republic of Ireland, scenario 0 ($y = 0$). Red and blue dots representing the origin and destination locations, respectively.

To further verify that the synthetic demand accurately represents the travel patterns in Ireland, the datasets (i.e. of y scenarios) were validated against the ED-to-ED commutes found in the training dataset [37]. This comparison resulted in an average correlation coefficient of 0.998, confirming that the generated spatial distribution of trips follows the training data. Further statistical validation using the Kullback-Leibler (KL) divergence resulted in a value of 0.03, indicating a strong resemblance between the commutes found in the synthetic and training datasets. This resemblance is visually confirmed in Figure 6, where the data points representing the computed number of commutes per Origin-Destination (OD) ED-pair align with the red dashed line, which defines a perfect match between the two datasets. The different colours of the data points represent the different scenarios (y).

B. Vertiport Allocation

As outlined in subsection V.B, the mean final vertiport network ($V_{\text{mean}}^{\text{final}}$) is established based on the successful agglomerative clustering scenarios. The resulting mean vertiport locations, alongside their corresponding contributing

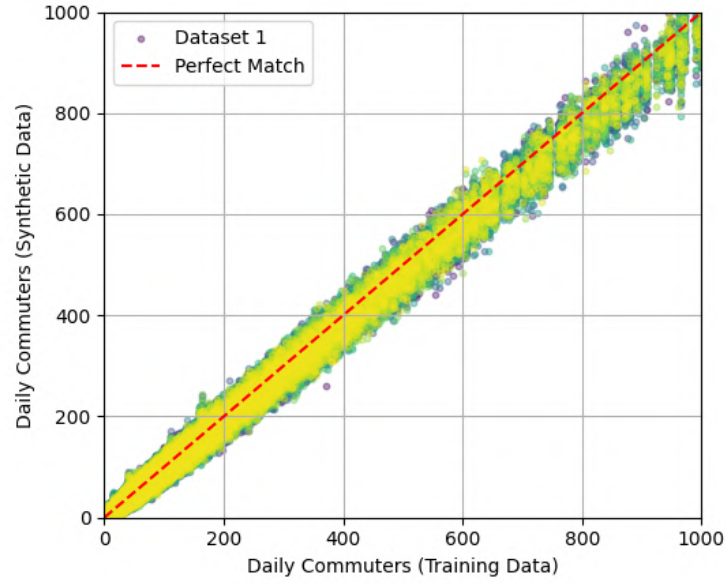


Fig. 6 Demand validation: Number of commutes between ED pairs; synthetic demand vs training demand data for scenario $y = 0, 1, \dots, 49$

cross-scenario locations, are visualized in Figure 7. This specific configuration then proceeds to the progressive elimination procedure, yielding the phased vertiport networks V^5 , V^{10} , V^{15} , and V^{55} , which are provided sequentially in Figure 8 through Figure 11, respectively. Each vertiport network is outlined below:

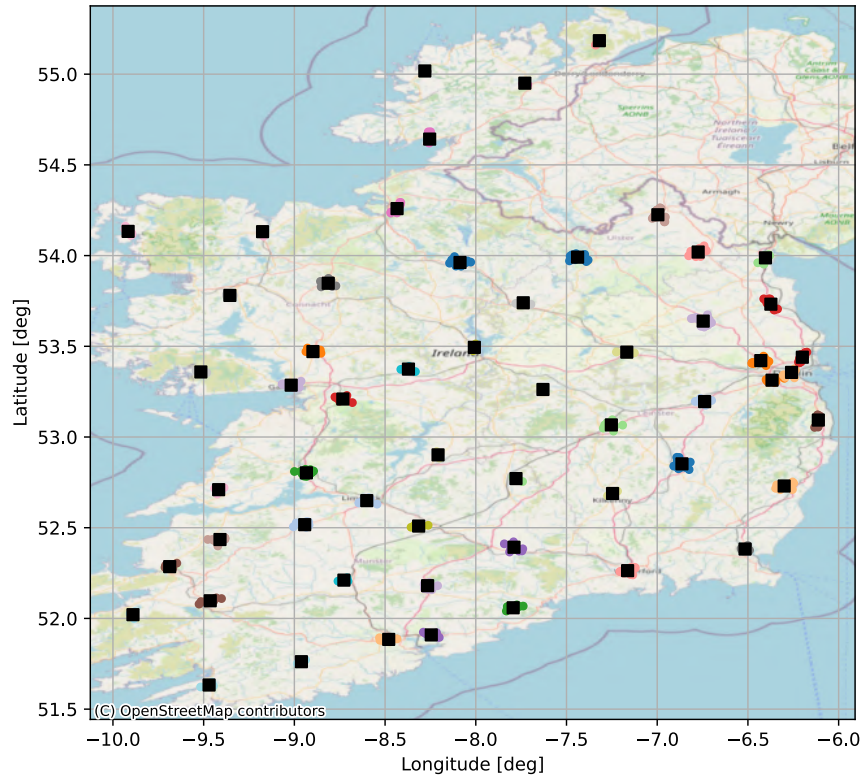


Fig. 7 Results of cross-scenario clustering and mean cluster locations of final network $V_{\text{mean}}^{\text{final}}$.

- **V¹⁰** The initial expansion phase, comprising 10 vertiports, is shown in Figure 9. The additional vertiports introduced in this stage are concentrated within the Dublin metropolitan area and its surroundings. This causes a reduction in the average distance between neighboring vertiports and allows for multi-rotor trips, establishing its operational appeal.

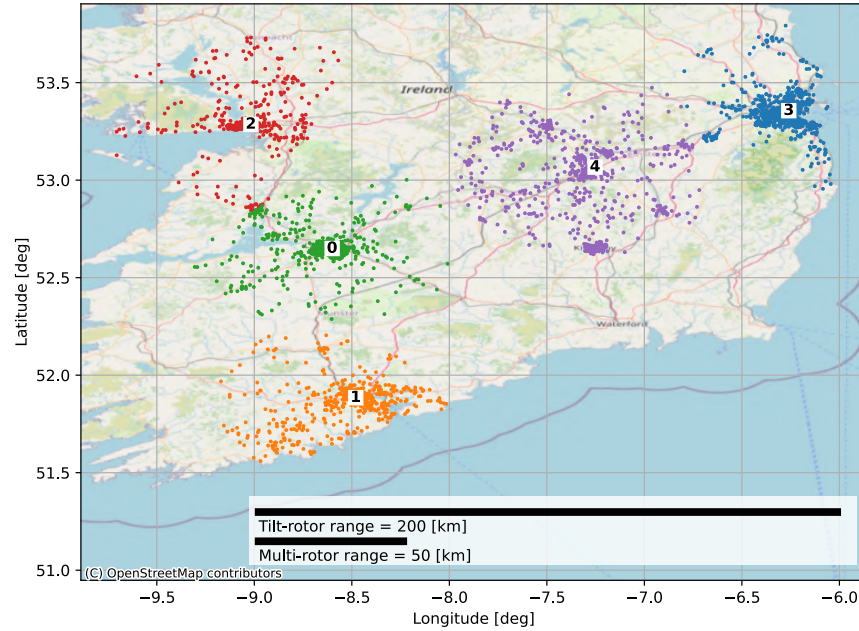


Fig. 8 5 Vertiport network, V^5

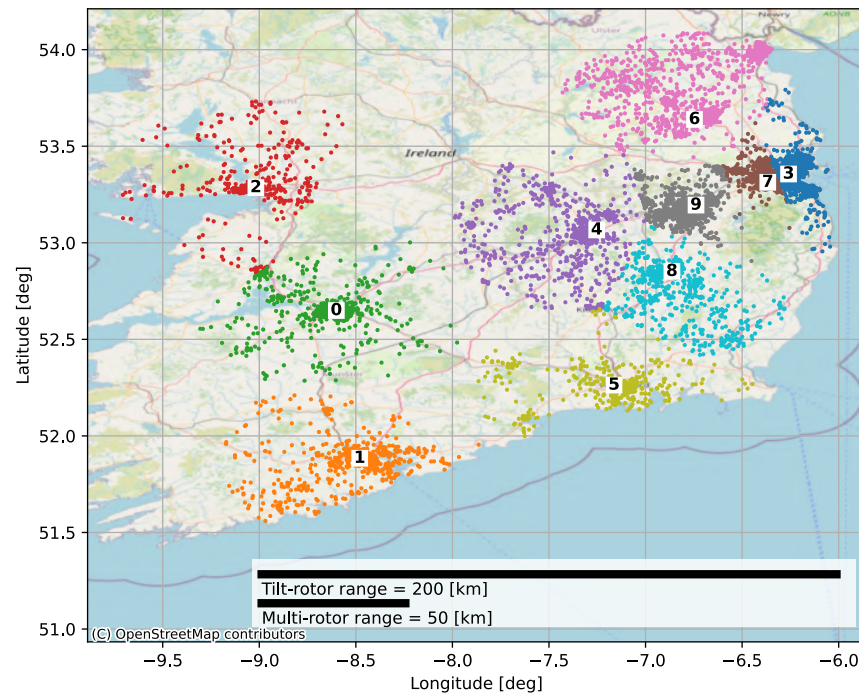


Fig. 9 10 Vertiport network, V^{10}

- **V¹⁵** Expanding the network from 10 to 15 vertiports primarily leads to an increase in regional air mobility trips.

This shift enhances the applicability of the tilt-rotor aircraft. An additional vertiport is also observed in Dublin at this stage, reinforcing the applicability of the multi-rotor aircraft. Overall, this phase of network development achieves nationwide coverage.

- **V⁵⁵** At this stage, the network has fully matured and encompasses 55 vertiports, providing complete coverage across Ireland. Furthermore, as visualized in Figure 11, vertiport concentrations can be observed within the three dense urban hubs: specifically, four vertiports serve Dublin (v_3, v_7, v_{14} , and v_{21}), three vertiports serve Galway and its surroundings (v_2, v_{44} , and v_{48}), and two vertiports cover Cork (v_1 and v_{28}). These concentrations form the optimal use case for the multi-rotor aircraft i.e. short-distance hops. Conversely, the spread of the remaining vertiports across the country facilitates longer-range regional trips, establishing the ideal operational environment for the tilt-rotor aircraft.

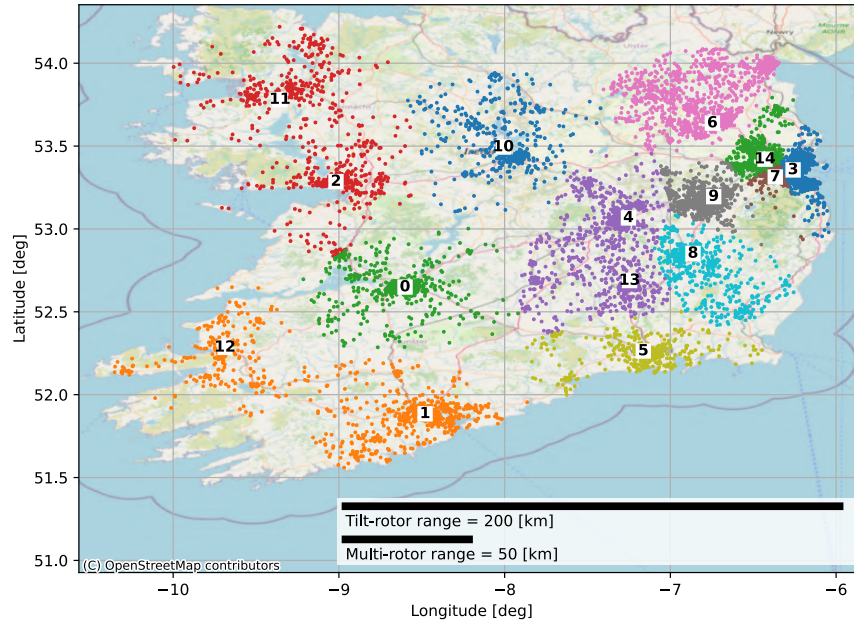


Fig. 10 15 Vertiport network, V^{15}

The distances between the vertiports as the network evolves are assessed and presented in Figure 12. R_{mean} indicates the average distance between vertiports in the network, while R_{netmean} represents the commute-averaged distance, and R_{min} defines the minimum distance between vertiports.

The coloured boxes constitute the ranges (at full capacity) for the multi-rotor (purple) and tilt-rotor (green) aircraft. Focusing on R_{min} for the network containing five vertiports, it is evident that the multi-rotor cannot perform any fully loaded flights, allowing the tilt-rotor to completely dominate this network configuration. Upon expansion to 10 vertiports, R_{min} decreases drastically, enabling the multi-rotor to begin serving trips. However, the applicability of the tilt-rotor aircraft remains clear due to its capacity to serve the majority, if not all, trips from the initial deployment until full system maturity.

C. Aircraft Performance

The most significant results of the aircraft sizing module (subsection V.C) are summarized in Table 6 and Table 7. Additionally, the power requirements for both aircraft across various loading scenarios are presented in Figure 13. Overall, the power requirements for the tilt-rotor are higher than those of the multi-rotor aircraft. This is primarily because of the larger rotor area of the multi-rotor, and consequently lower disk loading as opposed to the tilt-rotor aircraft. However, closer inspection reveals that the multi-rotor demands greater power during the cruise and reserve segments. This difference arises because the multi-rotor relies solely on powered lift throughout all flight phases, while the tilt-rotor leverages its wings for lift generation during cruise. This makes the tilt-rotor inherently more energy efficient in cruise, thus enabling it to cover greater distances. These findings confirm the optimal role of multi-rotors in serving short-distance hops, whereas the tilt-rotors optimally cover longer-range missions.

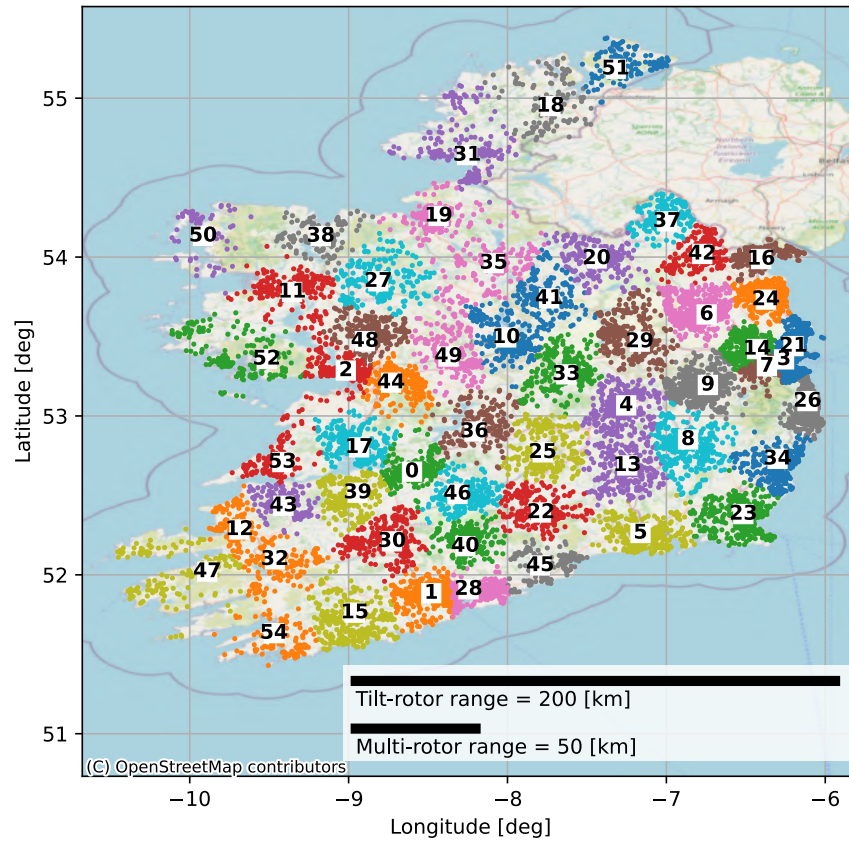


Fig. 11 55 Vertiport network, V^{55}

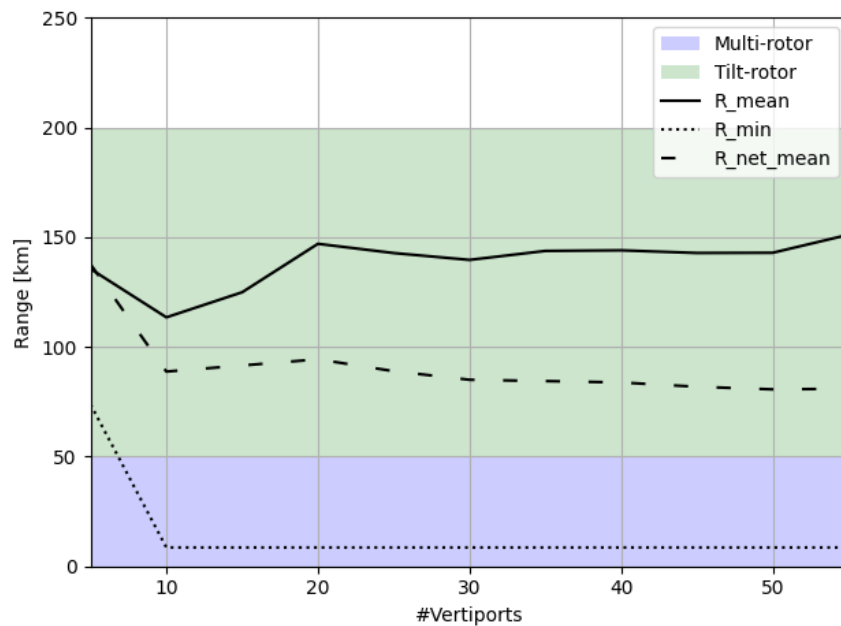


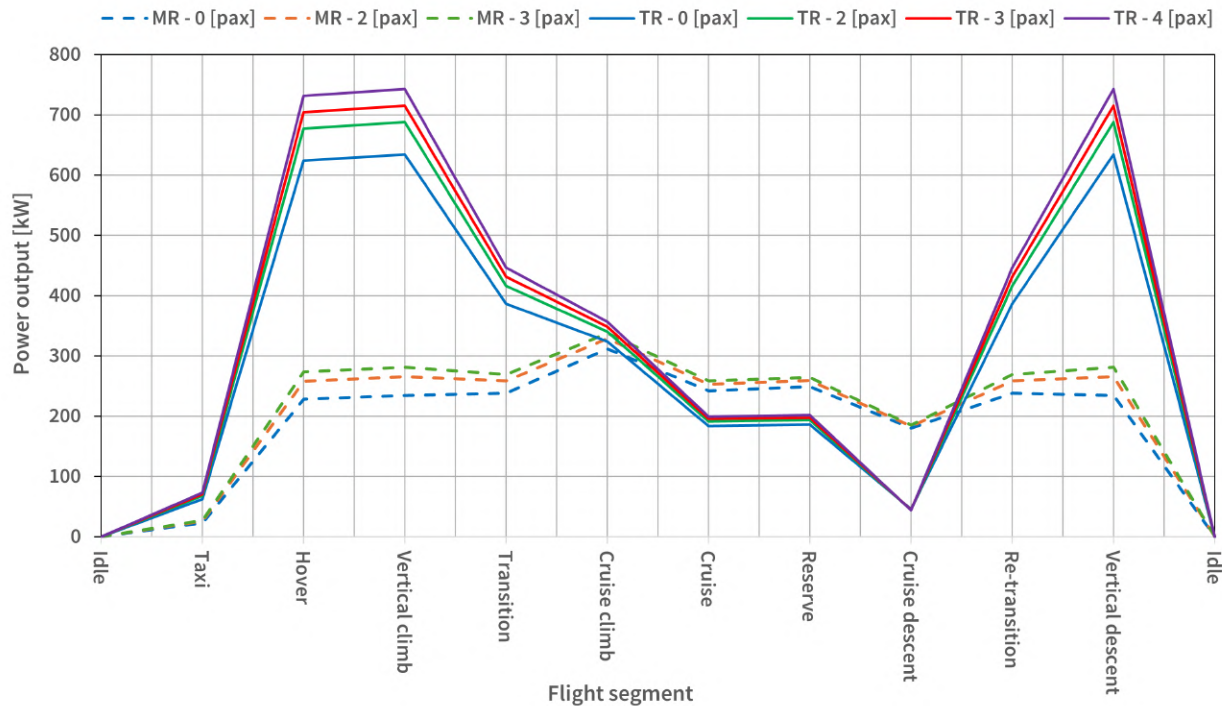
Fig. 12 Visualization of the distances between vertiports within each network configuration. The design cruise range of the multi-rotor and tilt-rotor aircraft are indicated through the purple and green blocks, respectively.

Table 6 VTOL-AD sizing results of the multi-rotor and tilt-rotor aircraft.

Variable	Multi-rotor	Tilt-rotor	Unit
Rotor diameter	2.5	3.2	m
Disk loading	221.1	670.6	N/m ²
Best endurance speed	23.7	47.8	m/s
Best range speed	31.2	62.9	m/s

Table 7 VTOL-AD mass sizing results of the multi-rotor and tilt-rotor aircraft.

	Multi-rotor		Tilt-rotor	
	Mass [kg]	Percentage of MTOM [%]	Mass [kg]	Percentage of MTOM [%]
MTOM	1992.0	100.0	3273.2	100.0
Payload mass	270.0	14.6	360.0	11.0
Empty mass	812.7	40.8	1646.4	50.3
Battery mass	909.0	45.6	1266.2	38.7

**Fig. 13 Power requirements of the multi-rotor and tilt-rotor aircraft per passenger loading scenario.**

D. Optimal Fleet Sizing and Composition

The optimal fleet growth path based on the performance metrics as defined in section IV is visualized in Figure 14 for the network configurations assessed in the ABS. Looking at the performance metric corresponding to the demand served, one can observe how the optimal fleet size starts at 425 aircraft for the V^5 network configuration and increases to 1000 once the network contains 10 vertiports. The heterogeneity factor is equal to zero for V^5 meaning a homogeneous tilt-rotor fleet (as expected based on the inter-vertiport distances as seen and elaborated upon in subsection VIII.B). It

increases to 0.35 for V^{10} and decreases to 0.2 for V^{15} . Optimizing energy efficiency leads to a fleet size of 25, which remains constant throughout the expansion of the vertiport network. This is expected seeing as it corresponds to serving the least amount of trips, and consequently, using the least amount of energy. The optimal heterogeneity factor results in a homogeneous multi-rotor fleet for V^5 , followed by a heterogeneous fleet with $\eta^* = 0.2$ for V^{10} and returns to a homogeneous multi-rotor fleet for V^{15} . Maximizing m_{LF} leads to an initial fleet size of 25 for V^5 , increases to 525 aircraft for V^{10} , and increases further to 600 aircraft for V^{15} . This fleet starts as heterogeneous with $\eta^* = 0.7$, after which it shifts to a homogeneous multi-rotor fleet for V^{10} , and remains the same for V^{15} . Seeing as the multi-rotor aircraft can transport 2 passengers, and the tilt-rotor 4 passengers, it is easier to fully load the multi-rotor aircraft. This is enhanced by the increased frequency of short trips occurring within the dense urban areas compared to longer (regional) trips. The last performance metric maximizes travel time saved. The resulting optimal fleet size starts at 525 aircraft for V^5 , increases to 1000 aircraft for V^{10} and remains constant. This fleet starts as a heterogeneous fleet consisting of primarily tilt-rotor aircraft for V^5 , shifts to a homogeneous tilt-rotor fleet for V^{10} , and maintains the homogeneous fleet for V^{15} . The preference for tilt-rotor aircraft is the result of its significantly higher cruise speed (65 m/s) compared to that of the multi-rotor aircraft (35 m/s).

After combining the performance metrics according to Equation 7, one arrives at the optimal fleet development plan presented in Figure 15. The optimal fleet is a homogeneous tilt-rotor fleet, irrespective of the network configuration. It starts with an optimal size of 400 aircraft for V^5 , which increases to 725 aircraft for V^{10} , and increases further to 1000 aircraft for V^{15} . The increase in fleet size corresponds to the overall observed increase in fleet sizes according to the performance metrics (m). The resulting fleet is homogeneous due to the combined effects of the demand served (m_{DS}) and time saved (m_{TS}) performance metrics, which favour tilt-rotor aircraft.

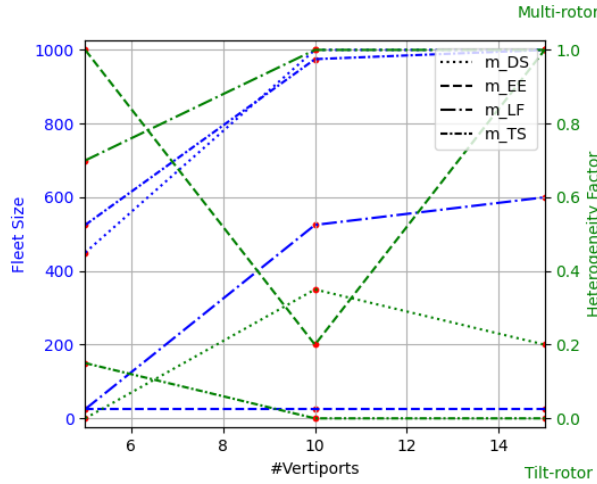


Fig. 14 Optimal fleet progression based on each performance metric (m) for network configuration V^5 , V^{10} and V^{15} .

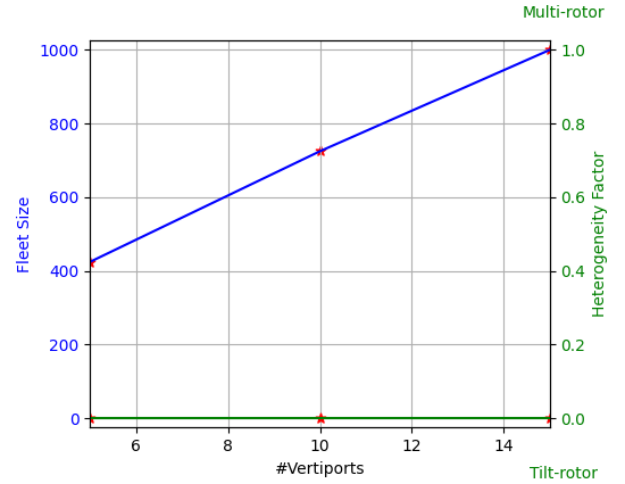


Fig. 15 Optimal fleet progression based on the Measure of Effectiveness (MoE) for network configuration V^5 , V^{10} and V^{15} .

IX. Discussion

This section contains a discussion on the results presented in section VIII, and its implications. It starts with the interpretation of the results in subsection IX.A, and continues with comparison of the results with existing literature. This is followed by the limitations and uncertainties of the established

A. Interpretation of Results

The framework successfully generates a demand-driven, phased network expansion plan. The rollout from 5 to 55 vertiports reflects a logical progression: beginning with a vertiport in each of the dense urban hubs (Dublin, Cork and Galway), expanding within the Dublin region, and eventually achieving national coverage. The progression is deterministic given the representative demand dataset but would be more dispersed and uncertain if applied to all 50 scenarios — an important distinction for risk analysis.

The optimal fleet is found to be a homogeneous one consisting of tilt-rotor aircraft, irrespective of the network

configuration size assessed in the ABS. The fleet size progresses from 425 to 1000 aircraft. This is a result of its superior revenue range and cruise speed, allowing to cover an increased amount of trips, and resulting in shorter trip times compared to the multi-rotor aircraft. However, the analysis of the optimal fleet growth path is constrained to three stages of vertiport network expansion. Accordingly, further analysis may result in a heterogeneous fleet, since the multi-rotor aircraft is superior when it comes to short hops (e.g. within dense urban hubs). This insight has significant procurement implications: operators should not assume a single optimal fleet configuration but should plan for evolution.

The number of take-off and landing pads may emerge as a critical constraint. Although realistic operations will need to account for a higher vertipad turnaround time, it is currently set to 15 seconds. This translates into a maximum of 240 take-off or landing procedures per vertipad. The number take-off and landing vertipads was set to 1 and 2, respectively. This was done deliberately to increase the likelihood of a landing pad being available when requested, and consequently, decrease the chance of an aircraft running out of energy during flight. This may be improved upon by adopting a dynamic pad allocator, which would allow for tracking of the required number of take-off and landing pads as the network evolves. Current implementation provides a feasible operational scenario, but dynamic pad allocation would allow for operators and regulators to budget for infrastructure evolution, and not assume static designs.

B. Practical Implications for AAM Deployment

This framework provides a top-level AAM deployment and expansion plan, and provides valuable insights for operators as well as regulators. Specifically for operators, the Ireland case study showed that in order to maximize AAM commute distance the phased network plan starts with high-density urban areas (e.g., Dublin, Cork, Galway), where tilt-rotor aircraft can achieve high load factors and time savings, demonstrating profitability early. Furthermore, it allows for planning of vertiport expansion (additional landing pads, takeoff capacity) to prevent congestion from creating operational risks and decrease value proposition. Delays in infrastructure upgrades will directly reduce served demand. Finally, it allows for the development of a fleet procurement strategy. In the case of Ireland, start with a fleet containing tilt-rotor aircraft and assess demand after a period of operation before committing to larger, potentially heterogeneous fleet deployments.

On the other hand, for regulators, the framework provides necessary insights on AAM operations, allowing for establishment of scalable certification pathways for vertiports, allowing operators to start with minimal infrastructure and expand based on demand. Furthermore, the framework can provide guidance to municipalities and operators, suggesting appropriate vertiport locations and spacing based on demand density and geographic characteristics. Although not assessed in current study, additional post-processing of the ABS operational data, allows for identification of high conflict zones. Furthermore, coupling with a noise analysis module would enable the assessment of the expected noise profiles. Finally, the framework allows for development of operational procedures and separation standards suitable for the chosen vertiport configuration, ensuring that safety is maintained even under congested circumstances.

C. Limitations, Uncertainties, and Model Fidelity

A number of simplifications have been employed in the demand model, resulting in a number of limitations: (1) the model captures only commute-to-work/school/college trips, whereas realistic AAM demand will include business travel, leisure, airport shuttles, and emergency services. This simplification likely underestimates the demand potential; (2) real demand will grow over time as trust increases and the AAM transportation system mature. Current study modelled a static demand level, which is appropriate for infrastructure sizing at a point in time but not for realistic long-term forecasting; (3) The model assumes passengers choose AAM if it saves time, without probabilistic weighting. Furthermore, it accounts for a 15% likelihood of choosing AAM [16]. In reality, risk aversion, cost sensitivity, and brand preference will reduce adoption below our estimates.

The operational limitations include: (1) the model does not simulate detailed flight paths, altitude separation, or interaction with existing manned aviation. Real-world airspace integration will add constraints; (2) We assume fixed turnaround times. Real processing times vary with passenger flow, security procedures, and baggage handling complexity; (3) the model assumes continuous VFR operations. Real networks will experience weather-induced cancellations, potentially requiring larger fleets and operational buffers.

D. Future Work

While this study provides crucial insights, the framework leaves room for a number of enhancements. Short-term improvements include extension of the entire evaluation to all 100 demand scenarios, computing statistical distributions

of optimal fleet size, composition, and network configuration. Current demand is modelled solely based on commute-to-work/school/college trips. Optimally the synthetic demand generation would incorporate multiple trip purposes (business, leisure, airport access), time-of-day variations, and seasonal patterns. By doing so, one could assess how network changes as the demand diversifies. Current modelling of the passengers is simplified, another improvement could be modelling of passenger security screening, baggage handling, and multi-modal ground connections (ride-sharing, transit), to assess how these affect turnaround times and fleet requirements. Lastly, one could integrate a financial model, which accounts for capital and operating costs for vertiports, aircraft, and support infrastructure to determine whether the AAM system amounts to an economically feasible and sustainable transportation system.

Long-term improvements include aircraft design and sizing co-optimization. Rather than fixing aircraft parameters, conduct a parameter sweep or optimization including vehicle design variables (MTOW, range, cruise speed, battery size) and network design. Furthermore, the ABS may be expanded to include multi-modal transportation, which includes modelling of the pre- and post-flight trips using ground transportation. This would allow for a more accurate estimation of the trip details of the alternative modes of transportation.

X. Conclusion

This paper presents a unified framework for designing scalable advanced air mobility (AAM) networks while optimizing heterogeneous fleet composition under operational constraints. The novelty of this study lies in the integration of three elements: (1) multi-scenario synthetic demand generation to account for variability; (2) scalable network allocation reflecting phased growth; and (3) agent-based simulation for assessment of operational feasibility and phased fleet sizing. The key contributions of this study include:

- 1) Replicability of the framework: The methodology is transparent, auditable, and applicable to any region with available commuting data. The Irish case study demonstrates the frameworks' applicability and feasibility at a national scale.
- 2) Phased Deployment Pathway: Rather than a single "optimal" network, the framework delivers a scalable roadmap showing logical expansion stages, supporting capital investment planning.
- 3) Operational Validation: By integrating constraints in the agent-based simulation (1 takeoff/2 landing pads, vertiport throughput, aircraft range), the framework assesses the operational feasibility of proposed networks.
- 4) Fleet Evolution Insights: The optimal aircraft growth path provides actionable guidance for procurement and asset planning.
- 5) Bottleneck Identification: The framework explicitly identifies infrastructure expansion requirements, enabling proactive capital planning.

This framework provides a structured tool for reducing the uncertainty in AAM deployment planning for investors, operators, and regulators. By basing decisions on demand data and operational simulation, it enables faster, more confident progression from conceptual design to infrastructure investment. The research confirms a fundamental principle: AAM network design cannot be decoupled from fleet operations and infrastructure evolution. Holistic, integrated planning is essential for sustainable deployment.

XI. Acknowledgements

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