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Intelligent Vertiport Traffic Flow Management for Scalable Advanced Air Mobility Operations

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***Abstract*—Advanced air mobility (AAM) operations will pose new challenges that require innovative air traffic management (ATM) and uncrewed aircraft system (UAS) traffic management (UTM) solutions. Notably, emerging vertiports must support vertical take-off and landing (VTOL) vehicles, on-demand AAM services, denser airspace volumes, and dynamic airspace structures. Additionally, traffic flow management systems must cater for stricter flight envelopes, micro-weather variations, small uncooperative aerial objects, limited vertiport occupancy, and battery restrictions of electric vehicles. This requires large volumes of unlabelled data that conventional algorithms cannot effectively process in a timely manner. This work thereby proposes a data model for vertiport traffic management, and investigates intelligent solutions to leverage this vast data infrastructure. It considers on-demand vertiport flight authorisation as a demonstrative use-case of emerging AAM requirements, and proposes a data model aligned with safety-layers and corridor-based airspace proposals in several global AAM concept of operations (ConOps). On-demand scheduling of electric VTOL (eVTOL) aircraft is first formulated as a constrained optimisation problem, and solved using mixed-integer linear programming techniques. The limitations of this approach are subsequently addressed through a deep reinforcement learning (DRL) solution that is quicker and more robust to system uncertainty. This investigation thereby proposes a pathway towards scalable, intelligent and multi-agent systems for AAM resource management and optimisation.**

***Index Terms*—Advanced air mobility, ATM, optimisation, reinforcement learning, UAM, UTM, vertiport**

I. Introduction

A. Advanced Air Mobility

The aviation industry is undergoing a digital transformation, marked by an unparalleled degree of innovation and infrastructural evolution. Specifically, the advanced air mobility (AAM) industry envisions an air transportation ecosystem for passengers and cargo, spanning urban, sub-urban and rural environments. This entails the introduction of a large and heterogeneous fleet of aerial vehicles that pose unique challenges to conventional aviation frameworks. Notably, the Federal Aviation Administration (FAA) indicates that most AAM vehicles will leverage vertical take-off and landing (VTOL) capabilities to support operations in urban environments with limited space for ground infrastructure [1]. Additionally, advancements in battery technologies, coupled with the drive to achieve net zero aviation, will result in the emergence of electric VTOL (eVTOL) vehicles [2].

B. UAS Traffic Management

As the AAM industry matures, conventional regulations, airspace structures and air traffic management (ATM) frameworks will prove inadequate in managing the increasing volumes of AAM traffic [3]. Consequently, increased autonomy is inevitable to support a safe and secure ATM infrastructure [4]. A global research effort is therefore underway to develop new uncrewed aircraft system (UAS) traffic management (UTM) solutions that address the unique requirements and challenges posed by AAM [5]. UTM, in fact, is complementary to ATM and involves the safe, efficient, collaborative and cost-effective management of UAS and AAM operations [6].

UTM systems must adhere to stringent flight envelopes and battery constraints imposed by emerging vehicles, which range from small delivery UASs to large air taxis. Notably, multiple designs exist within each vehicle category, leveraging different propulsion systems, materials, and communication, navigation and surveillance (CNS) technologies [7]. Furthermore, AAM fosters innovation through a federated infrastructure [8], such that new vehicles will be introduced as certification procedures become more accessible and streamlined. Each distinct vehicle design, however, requires tailored UTM operations for scheduling, separation assurance, and mission execution, posing a significant challenge to the UTM ecosystem.

To address this challenge, CAP2538 recommends that vertiports are made aware of individual aircraft performance capabilities to efficiently manage UAS and AAM operations [9]. Additionally, all information must be consolidated with data obtained from ground-, air-, and satellite-based sensing systems. Such data may lack specific labels or annotations required to train supervised machine learning (ML) models. UTM systems must therefore process and interpret substantial amounts of unlabelled data to ensure the safe and efficient scheduling and management of AAM resources [10].

C. Contributions

Reinforcement learning (RL) offers a promising solution to intelligently manage unlabelled AAM and UTM data. To date, however, little research has been conducted to investigate the potential of using RL for vertiport traffic flow management. Moreover, existing studies have not fully accounted for the unique challenges and requirements inherent to AAM.

A systematic review by Razzaghi et al. [11] highlights the successful application of RL in various aviation domains. Specifically, Xie et al. [12] demonstrate how RL enhances safety, efficiency, and resilience to uncertainties in traffic flow management for low-altitude UAM operations. Kumar et al. [13] further propose a novel RL-based approach for vertiport scheduling and showcase its ability to generalise to new and unseen operating scenarios. Their work, however, overlooks the impact of vertiport operations on neighboring AAM traffic and does not account for the limited availability of pads or corridors. Moreover, their solution is not consolidated with a robust data model for vertiport traffic management.

To address the shortcomings in existing literature, this research explores intelligent solutions to leverage unlabelled data and optimise nascent AAM operations. Specifically, it considers the authorisation of on-demand vertiport flights as a demonstrative use-case of Urban Air Mobility (UAM), a subset of AAM concerned with urban environments. A comprehensive data model for vertiport traffic flow management is proposed, and aligned with global AAM and UAM concept of operations (ConOps). Deep RL (DRL) is subsequently identified as a promising solution to transform this unlabelled data space into actionable decisions, enabling safe and efficient resource management. This approach is compared to conventional procedural and linear optimisation algorithms, to highlight the benefits of DRL in building a scalable and intelligent ATM and UTM framework. The main contributions of this work are as follows:

- A data model is proposed to support vertiport operations within an emerging AAM ecosystem. This is aligned with corridor- and layer-based airspace structures explored in global AAM and UAM ConOps, and embedded within a custom simulation environment;
- On-demand vertiport flight authorisation is first formulated as a constrained linear optimisation problem, which explicitly considers different mission priorities, limited vertiport resources and dynamic airspace corridors;
- DRL is then demonstrated to offer a more scalable and robust solution to the same authorisation problem when compared to procedural and optimisation-based solutions. The findings of this evaluation guide future research directions to enhance the effectiveness, safety, and reliability of intelligent solutions for AAM.

D. Paper Structure

Section II discusses AAM airspace structures and vertiport traffic management proposals in existing literature. Section III introduces a data model for vertiport operations and proposes the use of optimisation and DRL techniques for on-demand vertiport flight authorisation. Finally, Section IV evaluates the implemented techniques through a set of numerical experiments, and Section V summarises the main conclusions of this work to identify promising avenues for further research.

II. Background

A. Airspace Structures for AAM

Structuring very low-level (VLL) airspace for AAM remains a challenging task. The FAA UAM ConOps [1] introduces the corridor-based approach illustrated in Fig. 1, with one-way traffic and vertical or lateral passing zones. Similarly, Amazon [14] proposes a layered structure that separates high-speed vehicles and low-speed transit operations, as depicted in Fig. 1. Bauranov et al. [3] conduct a comprehensive review of airspace structure proposals, highlighting that ONERA, JAXA UTM, Nanyang Technological University, Airbus, and Embraer-X all advocate layer- or corridor-based airspace structures for AAM. Furthermore, the Metropolis project [15] compares different airspace structures and concludes that a layered approach strikes the best balance between safety, noise reduction, capacity, and efficiency. The Air Mobility Urban - Large Experimental Demonstrations (AMU-LED) project by the Single European Sky ATM Research (SESAR) also advocates a corridor-based airspace structure, as depicted in Fig. 2 [16]. This involves distinct high performance (HPL) and standard performance (SPL) layers, dedicated for high-performance vehicles and smaller UASs, respectively [17].

In a layer- or corridor-based airspace, higher altitude vehicles need to take-off and land at vertiports. AMU-LED proposes authorising dynamic corridors to connect the HPL and vertiport airspace, during which SPL traffic is restricted. If the vertiport is located near aerodromes, the vertiport operator must first obtain the necessary authorisation from air traffic control (ATC), as confirmed in CAP2538 [9]. Initially, corridors will require large safety buffers to accommodate AAM vehicle specifications and positioning uncertainty. As vehicle performance improves, the AMU-LED project envisions that corridors will transition to dynamically geo-fenced volumes that hinder, but do not completely restrict, SPL traffic.

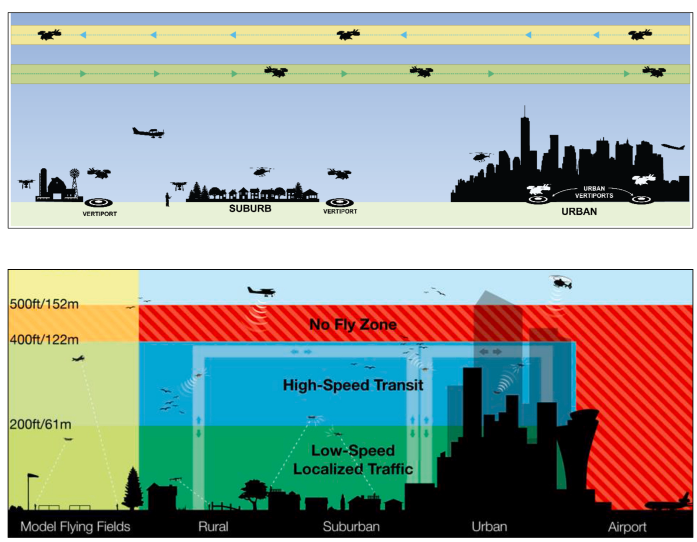

Fig. 1. Airspace structures proposed by the FAA [1] (top) and Amazon [14] (bottom).

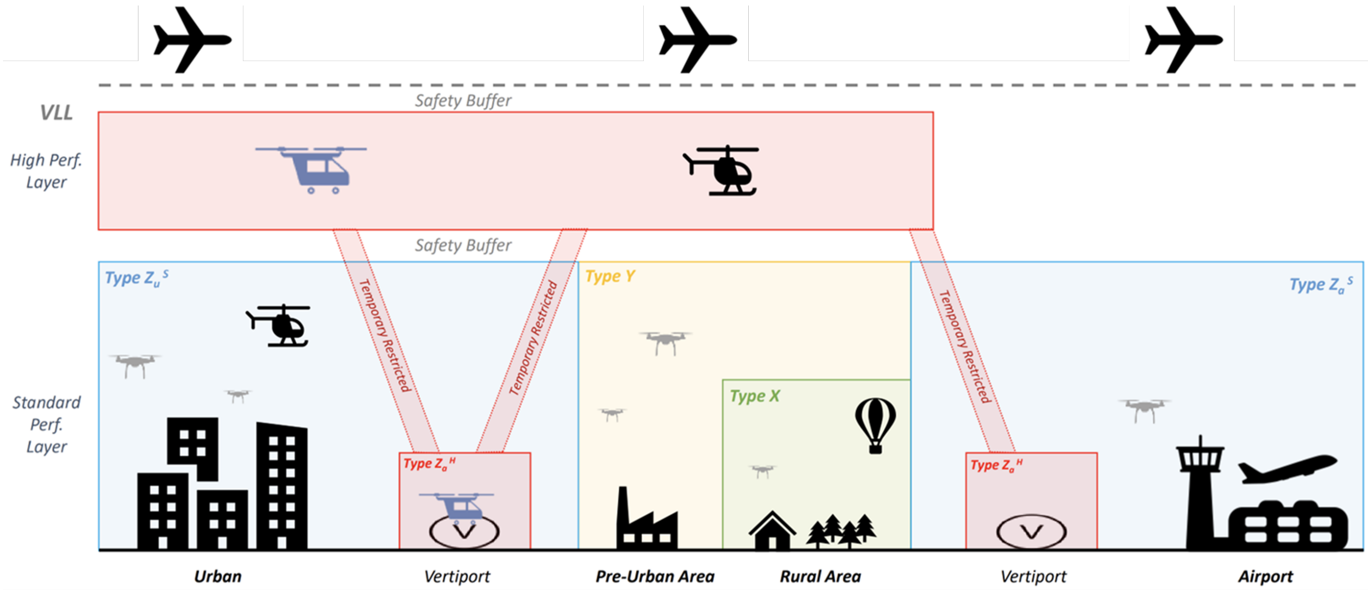

Fig. 2. Layered airspace structure proposed in AMU-LED, including dynamic corridors for vertiport take-offs and landings [16].

B. Vertiports

Vertiports play a crucial role within AAM and UAM ecosystems. While preliminary guidelines and considerations for vertiport designs have been published by the FAA [9], CAA [18], and EASA [19], further regulations are required to manage their operational procedures. In general, these documents introduce a final approach and take-off area (FATO) and safety area (SA), with an approach/departure slope to structure the terminal airspace surrounding a vertiport. Nonetheless, these concepts do not contradict the dynamic corridor concept presented by the AMU-LED project. Specifically, a dynamic corridor will only be activated once a vehicle departs the terminal airspace surrounding the vertiport.

Vertiports must incorporate charging facilities and remain as agnostic as possible to different vehicle designs. Notably, small urban vertiports will be constrained by a limited number of pads and charging bays. Furthermore, the number of dynamic VLL corridors will be limited due to large associated safety buffer volumes, and privacy concerns surrounding low-altitude corridors in urban areas. Operational procedures must also be developed to accommodate on-demand services such as air taxis and medical supply deliveries.

C. Vertiport Traffic Flow Management

Existing research on vertiport scheduling primarily focuses on separation assurance. Guerreiro et al. [20] investigate a first-come first-served (FCFS) scheme to assess the capacity and throughput capabilities of different vertiport designs. Conversely, Shao et al. [21] propose an adaptive control system to schedule terminal operations across multiple vertiports. Kleinbekman et al. [22] also formulate the sequencing of on-demand eVTOLs as a constrained optimisation problem to optimise schedules based on energy-efficient trajectories. The authors extend their work in [23] by introducing a rolling-horizon sequencing approach to schedule arriving and departing on-demand eVTOL flights. Similarly, Chen et al. [24] and Pradeep et al. [25] propose optimisation-based solutions for on-demand vertiport scheduling, while Song et al. [26] compare multiple sequencing approaches for multi-copter UAM applications.

These studies organise the vertiport airspace using stacked concentric rings, as depicted in Fig. 3. They introduce fixes, transit points and metering gates to manage arrivals and departures, along with holding stacks to absorb in-air delays. These proposals, however, are not aligned with the layer- and corridor-based airspace structures advocated in AAM and UAM ConOps. Consequently, their objective functions to not consider the impact of flight authorisations on air traffic in other AAM corridors and layers. Additionally, these works do not account for different mission priorities or limited vertiport resources. Incorporating micro-weather predictions, coverage information and other data sources presents further challenges to conventional optimisation approaches, and these algorithms will struggle to efficiently manage vertiport traffic when scaled to multi-vertiport environments with dense AAM traffic.

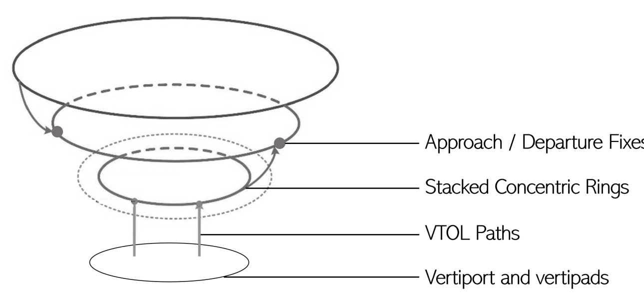

Fig. 3. Generic ring-based proposal to structure vertiport airspace.

D. Intelligent AAM Solutions

In recent years, significant progress has been made in the fields of artificial intelligence (AI) and ML. In fact, intelligent systems can significantly enhance AAM operations through a scalable and data-driven framework. Notably, RL can optimise vertiport flow management by transforming an unlabelled data space into a set of actionable decisions. This involves an agent iteratively exploring and exploiting its environment to learn optimal policies through trial and error. The agent can adapt to changing environmental conditions, making the system more robust to inherent system uncertainties. Moreover, trained RL models can quickly identify optimal actions in complex environments. In particular, DRL introduces a neural network to approximate the optimal policy function, supporting efficient training in environments with a large state space. Additionally, training can be performed offline, enabling an RL agent to leverage historical data when learning optimal policies. RL approaches can also be extended to multi-agent environments, facilitating collaborative decision-making for improved efficiency in a connected network of vertiports.

AAM operations challenge conventional Q-networks due to the presence of random flight patterns and environmental variations. Nonetheless, DRL techniques can learn successful policies directly from high-dimensional sensory inputs. The action-observation pairs of the agent are stored in an experience replay buffer and randomly sampled during training. This process breaks the correlation between consecutive experiences and avoids the issues of learning from non-stationary and highly correlated data. It allows the network to learn from a more diverse and representative set of experiences, leading to more stable and effective training [27]. This renders DRL particularly suitable for intelligent AAM frameworks.

III. Problem Formulation

A. Vertiport Data Model

Vertiports can leverage the data infrastructure illustrated in Fig. 4 to enhance their operations. As UTM users, communication with UTM systems and stakeholders is crucial for coordinated management of the AAM ecosystem. This includes receiving updates on airspace changes and geo-fences from UTM service providers (USPs) and coordinating with neighboring aerodromes and ATCs, especially when authorising AAM corridors in adjacent airspace volumes. Coordination with vehicle ground control centres and networked vertiports can further optimise traffic flow management through distributed information sharing and improved scheduling capabilities. This communication can be facilitated by a common information service provider (CISP) or the USP itself, using a flight information management system (FIMS) for bi-directional communication with the CISP or USP [28].

Supplementary data service providers (SDSPs) also play a vital role in optimally managing vertiport operations. Real-time information on AAM traffic, for instance, can help minimise delays and safety hazards. Similarly, data on the CNS-information (CNSI) infrastructure can help vehicles avoid regions of high electromagnetic interference or low service coverage. Additionally, vertiports can identify patterns in infrastructure variations by leveraging historical data, enabling them to preemptively optimise AAM traffic routes. Electric infrastructure should also be monitored, to cater for the impact of power disruptions on the charging capacity of vertiports.

Monitoring rail, ground and sea transportation further enables vertiports to estimate and predict travel demands. A train strike or road accident, for instance, will boost air taxi demands, while airspace disruptions may render an AAM operation less efficient. This paves the way for a collaborative multi-modal decision-making framework that maximises travel efficiency across various transportation domains. Additionally, it improves the business case for AAM by allowing companies to optimally manage a combined fleet of air and ground vehicles. Similarly, it enables more efficient cargo deliveries, especially when last-mile UAS deliveries depend on goods received over land or sea transport systems.

To ensure safety, a minimum vertiport sensing infrastructure is necessary to complement SDSPs. This includes micro-weather sensors and primary radar to accurately record safety-critical information within the vertiport surroundings. Uncooperative aerial entities and micro-weather variations can otherwise pose safety risks to AAM aircraft, and temperature fluctuations can impact the performance of electric vehicle batteries. A vertiport may further request support from security services with counter-UAS (C-UAS) capabilities. Telemetry data packets from cooperative AAM vehicles are also crucial for safe and autonomous vehicle identification. These enable a vertiport to understand the unique specifications of each aircraft and tailor an appropriate operational procedure based on surrounding environmental conditions. Such information includes mission priority, battery status, battery life requirements, and vehicle characteristics. Alternatively, mission priorities can be communicated by the USP or CISP.

B. On-demand Flight Authorisation

A subset of the proposed data model is used to explore DRL as a robust solution for vertiport traffic management. Specifically, this research focuses on authorising on-demand flight requests at a stand-alone and resource-constrained vertiport. For simplicity, the model does not consider the relationships between passenger demands and other contextual information. Consequently, flight requests are randomly generated, and do not consider fluctuations in travel demands, or disruptions in rail, sea and ground transportation systems. Additionally, it assumes that a vehicle is ready for take-off or landing as soon as it submits a request, without the ability to schedule future time slots. The vertiport is also assumed to be situated in a segregated airspace volume, eliminating the need for ATC authorisation when scheduling a dynamic corridor.

1) Vertiport resources: The vertiport is assumed to have a fixed number of pads, each capable of accommodating only one vehicle at a time. Unlimited charging and parking bay capacity is also assumed, but future studies can readily incorporate additional constraints to limit this vertiport resource.

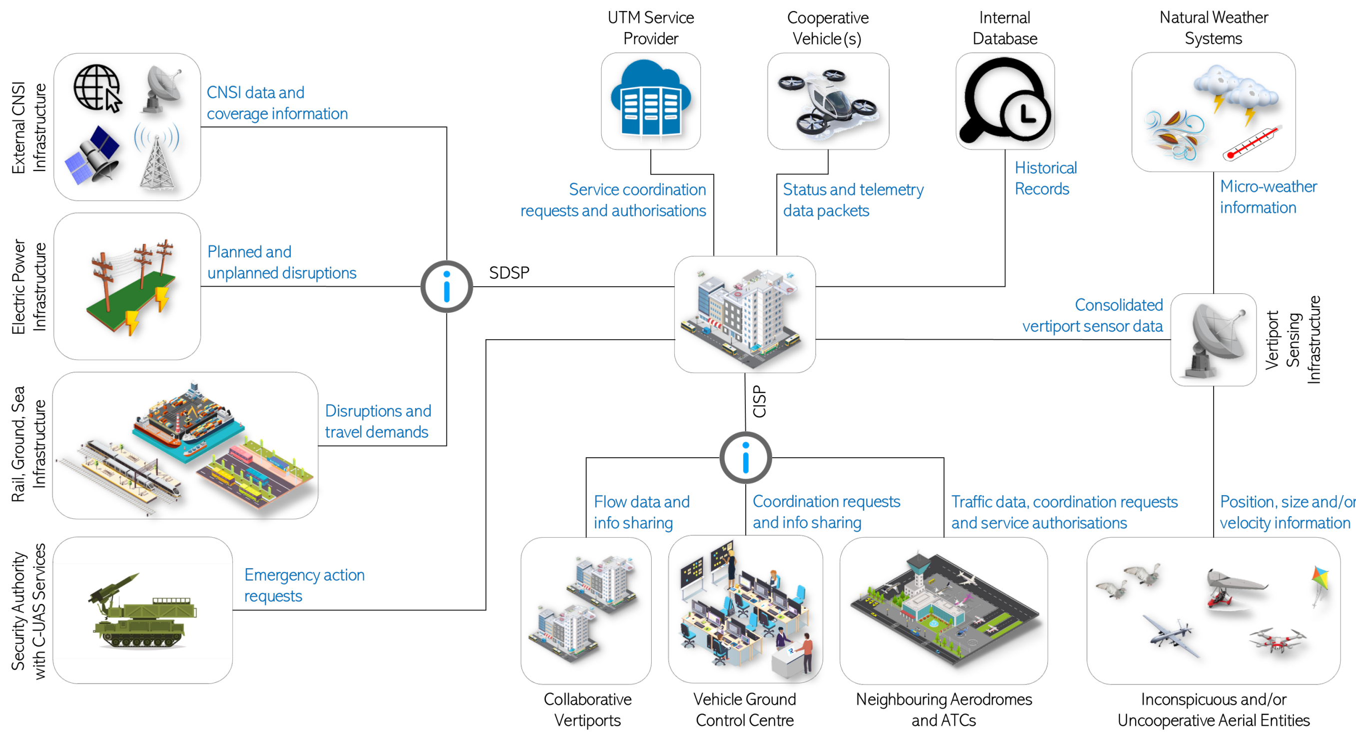

Fig. 4. Proposed data model for vertiport flow management.

2) Dynamic corridors: The model adopts the corridor-based structure proposed in AMU-LED. For safety, privacy, and traffic disruption considerations, only two corridors are assumed, shared by arriving and departing aircraft. Moreover, only one vehicle can travel through a dynamic corridor at a given time. If multiple vehicles traverse different corridors simultaneously, however, it is assumed that they can maintain sufficient spatial separation in the vertiport terminal airspace. Nonetheless, these assumptions can be readily modified in future studies to reflect the safety requirement of different ConOps and environments.

3) Procedures: Each flight requires a certain amount of time to traverse its assigned corridor after take-off or before landing. This duration varies for each vehicle-corridor combination and includes the time needed for a vehicle to reach the beginning of the corridor from its current position. For simplicity, the model does not account for the impact of micro-weather variations on travel duration. Similarly, each flight requires a specific on-pad sequence time before take-off or after landing, which is assumed to be the same for all pads. Future work may also consider vertiports with different classes of pads, suitable for different vehicle operations. To ensure safer operations, a pad is considered occupied from the moment a vehicle is authorised to use it. In contrast, a corridor is only considered occupied when the vehicle has started flying in or toward the corridor. For the purpose of sequential decision-making, the model further assumes that only one operation can be authorised at a given time. This has negligible impact if a sufficiently small time step is considered.

4) Airspace constraints: The USP may impose additional airspace constraints to safely manage AAM traffic. An HPL density limit is thereby assumed, which restricts the number of vehicles allowed in the HPL corridor at any given time. This limit is initially set to an arbitrary value, incremented when a flight departs to the HPL corridor, and decremented when a flight lands from the HPL corridor. For simplicity, air traffic from other sources is not considered.

5) Mission priorities: Each vehicle is assigned a priority level, with higher numbers indicating higher priorities. The prioritised delay of a vehicle is thereby defined as the product of its actual delay and priority level. An arbitrary maximum priority level of 3 is considered, with a uniform and random distribution of different flight priorities.

6) Battery life: Each electric vehicle transmits its battery status when submitting a flight request, and battery charging and discharging is modelled for departing and arriving aircraft, respectively. Additionally, arriving vehicles are assumed to require a specific battery percentage to traverse each corridor, such that a catastrophic failure occurs if a vehicle has insufficient battery to traverse any available corridor. This leaves sufficient time for appropriate contingency maneuvers before the vehicle completely runs out of battery.

C. Vertiport System Objectives

A vertiport must maximise throughput, minimise delays and airspace disruptions, and adhere to safety and airspace capacity constraints. It must also consider mission priorities when evaluating the impact of flight delays, as shown in Fig. 5.

Fig. 5. Considerations of a vertiport management system.

Safety inevitably retains the highest priority in a vertiport management system. To prevent accidents, a crash is assumed to occur if a vehicle is authorised to take-off or land in an unavailable pad or corridor. Additionally, a catastrophic event occurs if an arriving vehicle has insufficient remaining battery to land using any available corridor. For simplicity, safety concerns surrounding micro-weather variations and corridor intrusions by uncooperative entities are not considered. Furthermore, dependencies between battery fluctuations and weather or temperature conditions are disregarded. Moreover, both dynamic corridors are assumed to intersect a single SPL corridor, such that AAM traffic disruptions can be reduced by minimising the duration for which one or both corridors are active. The model thereby focuses on minimising prioritised delays, while ensuring safe operations and minimising traffic disruptions. Nonetheless, future work can readily introduce more complex models and objectives.

D. Constrained Linear Optimisation Formulation

Authorisation of on-demand vertiport flight requests is first formulated as a constrained linear optimisation problem. To account for a dynamically changing list of pending flights, the resulting algorithm is called at each time step, or whenever a new flight request is received. This must respect a comprehensive set of safety constraints while minimising flight delays and AAM traffic disruptions in the SPL.

1) Variables: A decision variable $x_{f,c,p,t}$ is defined as:

$$x_{f,c,p,t} = \begin{cases} 1 & \text{if } f \text{ authorised to } c \text{ and } p \text{ at } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $f \in F$, the set of all pending flights in the queue; $c \in C$, the set of all available corridors; $p \in P$, the set of all available pads; and $t \in T$, the set of all possible authorisation times and the simulated time window. This is complemented by the auxiliary variable y_t, defined as:

$$y_t = \begin{cases} 1 & \text{if any } f \text{ occupies any } c \text{ at time } t \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

2) Objective Functions: Two objective functions are defined as (3) and (4) to respectively minimise the sum of prioritised delays and SPL disruptions:

$$\min \left[\sum_{f,c,p,t} x_{f,c,p,t} \left(t - t_f^r \right) \left(i_f \right) \right] \tag{3}$$

$$\min \left[\sum_t y_t \right] \tag{4}$$

where t_f^r is the time at which flight f submitted a request, and i_f is the importance or priority of flight f. These can be combined as a hierarchical set of objectives with different priorities, or as a single weighted objective function.

3) Constraints: Each flight must be authorised to exactly one pad and one corridor at one time instant, such that:

$$\sum_{c,p,t} x_{f,c,p,t} = 1 \; \forall \; f \in F \tag{5}$$

Additionally, the battery limitations of arriving aircraft must be respected, according to:

$$\sum_t x_{f,c,p,t} t \leq t_{f,c}^{max} \; \forall \; f \in F | a_f = 1, \; c \in C, \; p \in P \tag{6}$$

where $t_{f,c}^{max}$ is the maximum time at which flight f can be authorised to corridor c, deduced from the aircraft battery status, vehicle battery model and time required to traverse each corridor; and a_f is a binary parameter equal to 1 if flight f is requesting to land and 0 if it is requesting to take-off.

To ensure smooth scheduling of on-demand flights, it is crucial to avoid conflicts with previously authorised operations. Consequently, a flight can only occupy a specific corridor or pad after previously approved flights have traversed that corridor or pad, according to (7) and (8), respectively:

$$\sum_t \left(x_{f,c,p,t} \left[t - t_c^{min} + t_f^{pad} \left(1 - a_f \right) \right] \right) \geq 0 \quad \forall \; f \in F, \; c \in C, \; p \in P \tag{7}$$

$$\sum_t \left(x_{f,c,p,t} \left[t - t_p^{min} \right] \right) \geq 0 \; \forall \; f \in F, \; c \in C, \; p \in P \tag{8}$$

where t_c^{min} is the first time at which corridor c is available; t_p^{min} is the first time at which pad p is available; and t_f^{pad} is the duration for which flight f will occupy its assigned pad.

Flight authorisations must also respect the time required by each flight to traverse a corridor and complete its on-pad sequence. If two flights are assigned to the same corridor or pad, sufficient temporal separation must be guaranteed according to (9) and (10):

$$
\begin{aligned}
&t_2 \geq t_1 + \\
&\left[t_{f1,c}^{cor} + t_{f1}^{pad}\left(1 - a_{f1}\right)\right]\left[\sum_{p}\left(x_{f1,c,p,t1} + x_{f2,c,p,t2}\right) - 1\right], \\
&t_2 \geq t_1 + \\
&\left[t_{f2,c}^{cor} + t_{f2}^{pad}\left(1 - a_{f2}\right)\right]\left[\sum_{p}\left(x_{f2,c,p,t1} + x_{f1,c,p,t2}\right) - 1\right] \\
&\forall\ f_1 \in F - 1,\ f_2 \in [f_1 + 1, F], \\
&\quad t_1 \in T - 1,\ t_2 \in [t_1 + 1, T],\ c \in C
\end{aligned} \tag{9}
$$

$$
\begin{aligned}
&t_2 \geq t_1 + \left[t_{f1,c}^{cor} + t_{f1}^{pad}\right]\left[x_{f1,c,p,t1} + \sum_{c'} x_{f2,c',p,t2} - 1\right], \\
&t_2 \geq t_1 + \left[t_{f2,c}^{cor} + t_{f2}^{pad}\right]\left[x_{f2,c,p,t1} + \sum_{c'} x_{f1,c',p,t2} - 1\right] \\
&\forall\ f_1 \in F - 1,\ f_2 \in [f_1 + 1, F], \\
&\quad t_1 \in T - 1,\ t_2 \in [t_1 + 1, T],\ c \in C,\ p \in P
\end{aligned} \tag{10}
$$

where $t_{f,c}^{cor}$ is the duration for which flight f will occupy its authorised corridor after take-off or before landing. Moreover, the vertiport can only authorise one flight at a given time instant, according to:

$$
\sum_{f,c,p} x_{f,c,p,t} \leq 1\ \forall\ t \in T \tag{11}
$$

and an authorised flight must complete its sequence in the simulated time window, such that:

$$
\sum_{t,p}\left[x_{f,c,p,t}\left(t + t_f^{pad} + t_{f,c}^{cor}\right)\right] \leq T \qquad \forall\ f \in F,\ c \in C \tag{12}
$$

The scheduling system must also respect HPL density constraints, according to:

$$
d + \sum_{f,c,p,t1 \leq t}\left[x_{f,c,p,t}\left(1 - a_f\right) - x_{f,c,p,t}\left(a_f\right)\right] \leq D\ \forall\ t \in T \tag{13}
$$

where d and D are the initial and maximum HPL density, respectively. Finally, an SPL disruption occurs if any flight occupies any corridor at a given time instant, such that:

$$
\begin{aligned}
&y_{t2} \geq \sum_{p} x_{f,c,p,t} \\
&\forall\ t \in T - 1,\ t_2 \in [t, T] \,|\, \left(t_2 \leq t + t_{f,c}^{cor} \text{ and } a_f = 1\right) \\
&\quad \text{or}\left(t_2 \geq t + t_f^{pad} \text{ and } t_2 \leq t + t_f^{pad} + t_{f,c}^{cor} \text{ and } a_f = 0\right), \\
&\quad c \in C,\ f \in F
\end{aligned} \tag{14}
$$

E. Deep Reinforcement Learning Formulation

Conventional optimisation techniques will struggle to handle the computational complexity of multi-vertiport environments with extensive data inputs. Furthermore, such algorithms will struggle to handle system uncertainties, caused by procedural delays and stochastic environmental variations. To address these challenges, DRL offers a scalable and robust data-driven solution for vertiport management. The problem of on-demand vertiport authorisation is therefore approximated as a Markov Decision Process (MDP), characterised by a set of states, actions, transitions, and rewards.

The proposed DRL formulation is illustrated in Fig. 6. Incoming flights are pre-processed into sorted queues based on their corridor traversal times, on-pad sequence times, incurred prioritised delay, and remaining battery life. The agent selects which flight to authorise from the top of each queue, limiting the action space to $2(N+1)$ discrete actions for quicker training, where N is the number of available corridors. This further ensures a scalable decision-making approach as the complexity of the underlying problem increases. Additionally, each action is post-processed to assign the authorised flight to the next available pad and the nearest available corridor that the vehicle has enough battery life to traverse. This prevents the RL agent from explicitly assigning a corridor and pad to each flight, to enforce a safer and more scalable design.

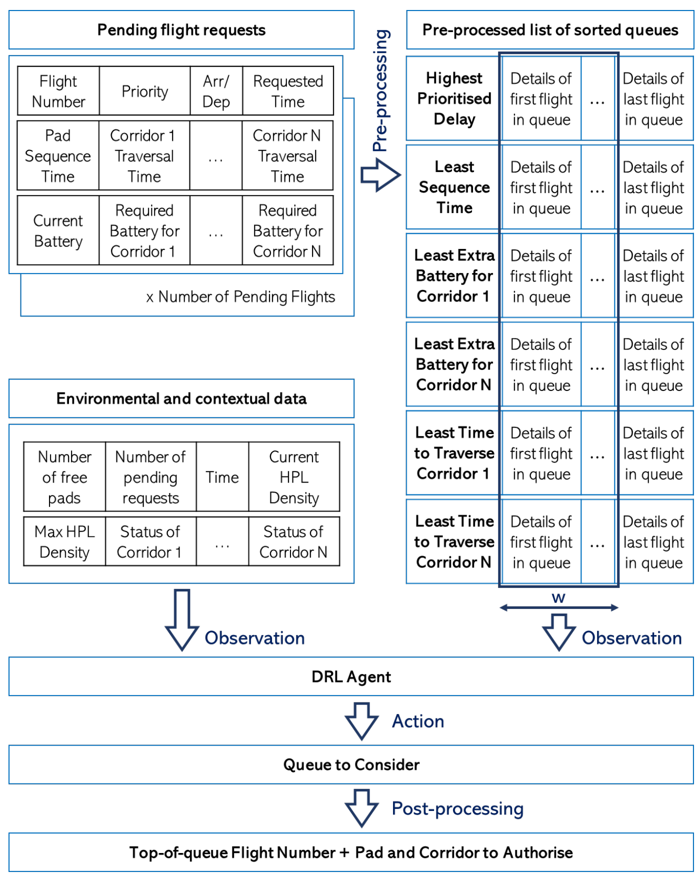

Fig. 6. Summary of proposed DRL workflow at each time step.

The state space of the MDP problem incorporates details of the top w flights in each queue, where w is a variable parameter. These details include the flight number, priority, status, requested time, sequence time, traversal time for each corridor, current battery life, and required battery life to traverse each corridor. An observation also includes information on pad availability, corridor availability, simulation time, number of pending vehicles, current HPL density, and maximum allowable HPL density. Future system upgrades may further include micro-weather information, radar outputs, and additional supplementary data in each observation, and incorporate pre-scheduled flights, communication with ATC and multi-vertiport collaboration to test and develop more sophisticated solutions. The action space can also be enhanced by increasing the number of flights that the agent can authorise to multiple elements within each queue. Moreover, a vertiport may be given the authority to explicitly reject a request if it is unable to safely land the vehicle before its battery runs out.

For demonstration purposes, a simple weighted reward function is defined as:

$$R = \underline{w}\ [s,\ c,\ b,\ h,\ i,\ t,\ v,\ d']^T \tag{15}$$

where R is the episode reward; and s, c, b, h and i are binary variables respectively set to 1 if a flight authorisation was successful, if a crash occurred, if an arriving vehicle ran out of battery, if the HPL density limit was exceeded, and if the SPL layer was interrupted; t is the time elapsed with no catastrophic events; v is the number of pending vehicles in the queue; d' is the maximum current prioritised delay; and $\underline{w}$ is a weight vector, tuned for the required performance specifications. Future system upgrades may employ more sophisticated reward functions or problem formulations to enhance safety and optimality, as discussed when evaluating the implemented proposal. An episode is terminated when a crash or battery loss occurs, or when a predefined time window elapses. Additionally, a large positive terminal reward is given if no catastrophic events occur throughout an episode.

IV. Experiments

A. Evaluation Environment

A custom openAI gym vertiport environment was developed to evaluate the vertiport management algorithms, as illustrated in Fig. 7. Flight requests with random parameters are randomly generated in the environment, and the agent can authorise up to one flight at each time-step. The state and action information is displayed, together with the current and accumulated rewards. All experiments were carried out on an 11th Gen Intel(R) Core(TM) i7-11370H @ 3.30GHz CPU, and all optimisation problems were solved using the commercial Gurobi solver.

B. Results

Each algorithm was evaluated across 500 simulations and compared in Table I. The employed metrics include the length of each episode; the percentage of episodes in which a crash or battery loss occurred; the number of disruptions, successful authorisations, and mean prioritised delay in each episode; and the latter three metrics normalised with respect to episode length. The following algorithms were evaluated:

- *Random*: Random action selection;
- *FCFS*: Procedural algorithm which authorises the first pending flight that submitted a request;
- *Highest prioritised delay first (HPDF)*: Procedural algorithm which authorises the flight incurring the HPD;
- *DRL 1*: DRL algorithm solely considering safety assurance ($\underline{w} = [15, -50, -20, 0, 0, 1, 0, 0]$);
- *DRL 2*: DRL algorithm minimising prioritised delays ($\underline{w} = [15, -50, -20, 0, 0, 1, 0, -0.1]$);
- *DRL 3*: DRL algorithm minimising prioritised delays and SPL disruptions ($\underline{w} = [15, -50, -20, 0, -3, 1, 0, -0.1]$);
- *Opt 1*: Optimisation algorithm with an objective function minimising prioritised delays;
- *Opt 2*: Optimisation algorithm with a hierarchical objective function minimising SPL disruptions (high priority) and prioritised delays (low priority).

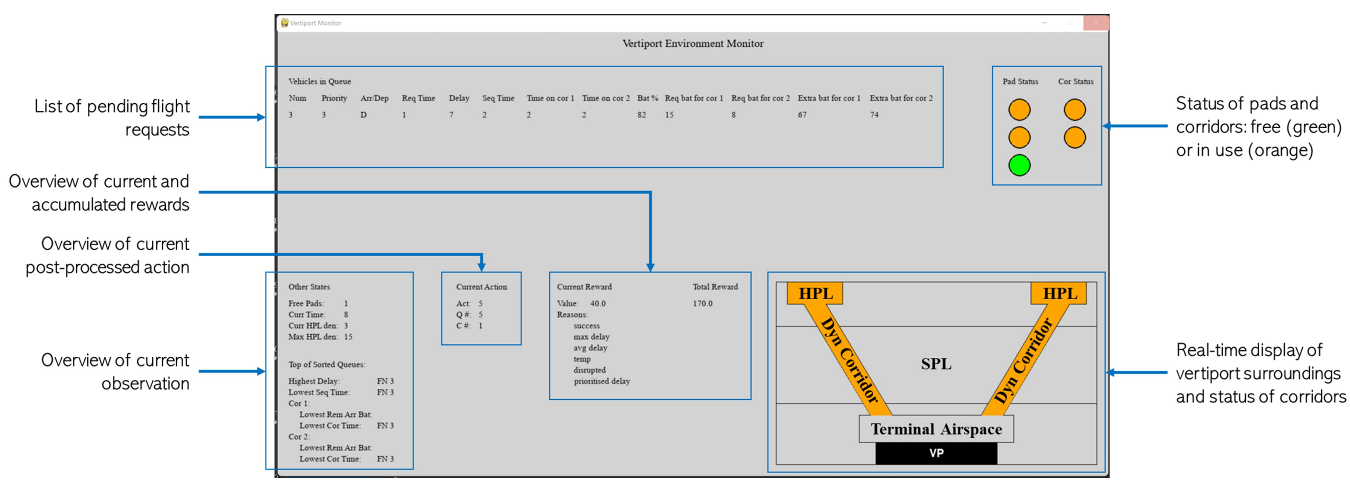

Fig. 7. Display of custom openAI gym vertiport environment used to evaluate the proposed vertiport management algorithms.

The impact of modifying the objective function of the optimisation algorithm is further illustrated in Fig. 9. Moreover, the computational time required by each class of algorithms is demonstrated in Fig. 10.

C. Discussion

The observed results suggest that all algorithms were appropriately designed and implemented. The mixed-integer constrained linear optimisation algorithm effectively scheduled and authorised on-demand vertiport flight requests based on the selected objective function. Notably, *Opt 1* marginally surpassed the performance of FCFS and HPDF algorithms, and *Opt 2* effectively minimised SPL disruptions, albeit at the expense of slightly higher average delays. Nonetheless, the algorithm execution time increased significantly as the number of pending flight requests increased, highlighting the limitations of conventional optimisation techniques for high volumes of AAM operations. In contrast, the DRL solutions showcased considerably lower execution times.

Within the DRL framework, different reward functions achieved the expected trade-offs between safety assurance, delay minimisation, and SPL disruption reduction. Moreover, the DRL agents reduced the number of crashes and increased the average episode length when compared to a random selection algorithm, confirming their ability to learn and improve performance over time. Notably, *DRL 1* successfully reduced the number of battery failures, even without explicit inclusion of the maximum allowable authorisation time in its observation space. By utilising raw battery readings and estimates for intelligent decision making, the DRL algorithm demonstrated its ability to reliably interpret unlabelled datasets. Moreover, *DRL 2* successfully reduced prioritised delays when compared to *DRL 1*, and *DRL 3* further reduced SPL disruptions.

Insufficient time elapsed within each episode of the random selection experiment for battery depletion, significant delays, or disruptions to occur. Consequently, even when considering normalised metrics, the results cannot be fairly compared to other algorithms with significantly longer episode lengths.

TABLE I
COMPARISON OF FLIGHT AUTHORISATION ALGORITHMS USING THE MEAN AND STANDARD DEVIATION OF MULTIPLE EVALUATION METRICS[a]

Algorithm	C [%]	BL [%]	L [steps]		S [#]		NS [%]		D [steps]		ND [%]		AD [steps]		NAD [%]	
			μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
Random	100	0	14.63	8.72	4.13	2.22	30	8	7.36	5.32	49	18	5.09	7.16	41	59
FCFS	0	44	49.51	15.18	16.63	5.62	33	5	34.48	11.70	69	10	13.92	9.83	35	31
HPDF	0	49	48.90	14.81	16.31	5.35	33	5	33.69	11.25	68	9	11.00	7.79	28	27
Opt 1	0	40	50.80	13.82	17.12	6.01	33	6	33.52	11.13	65	10	14.47	10.16	34	30
Opt 2	0	64	46.90	14.59	13.76	5.34	29	5	25.7	9.77	55	11	21.94	13.18	53	34
DRL 1	17	39	48.36	15.27	8.95	3.11	19	4	21.97	8.00	46	10	40.27	15.91	84	24
DRL 2	50	32	43.20	15.13	10.34	3.75	25	5	23.49	8.85	55	11	24.51	13.11	61	36
DRL 3	22	69	39.64	13.41	8.10	2.87	21	5	18.77	7.57	48	12	25.21	9.51	67	27

[a] where L is the episode length, C is the % of episodes ending in a crash, BL is the % of episodes ending in a battery loss, S is the number of successful authorisations, NS is the normalised % of successful authorisations, D is the number of SPL disruptions, ND is the normalised % of SPL disruptions, AD is the average prioritised delay, and NAD is the normalised average prioritised delay.

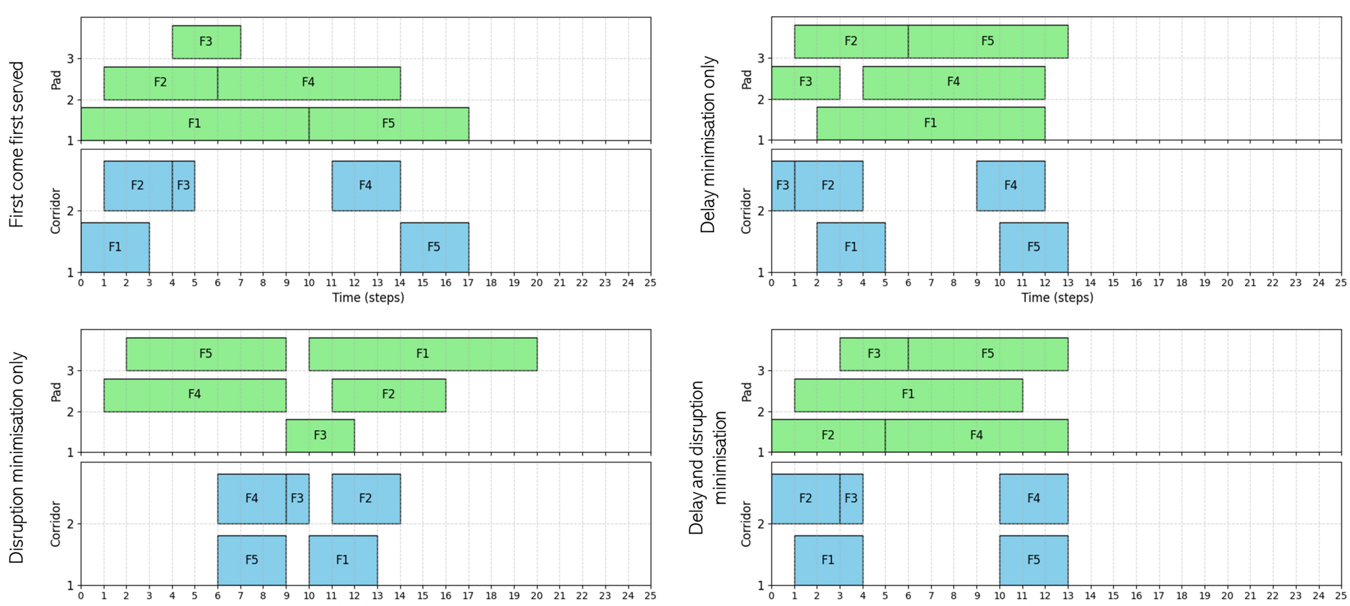

Fig. 9. Flight schedules generated by the optimisation algorithm at a single time instant, for the same set of flights but different objective functions.

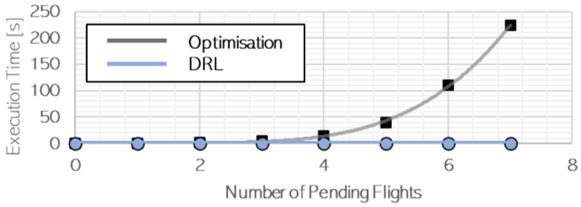

Fig. 10. Execution time of DRL and optimisation algorithms.

Despite achieving poorer success, delay and disruption metrics than other algorithms, DRL performance is expected to improve considerably with further training and a more refined reward function. In fact, the DRL results were observed to approach those of conventional algorithms, even after a few training iterations. Nonetheless, refining the DRL agent falls beyond the scope of this work. Conversely, these experiments showcased the suitability of DRL as a scalable alternative to procedural and optimisation-based techniques, that can effectively handle vast quantities of unlabelled data. Moreover, theory suggests that DRL agents are more resilient to system uncertainties, a hypothesis that will be tested in future work.

Nonetheless, incorporating delay or disruption minimisation in the reward function was observed to compromise system safety. Safe RL techniques must therefore be explored to ensure safe operations while maintaining near-optimal results. Explainable RL techniques can also be used to promote a transparent RL model and enhance system trustworthiness.

V. Conclusion

This work proposed a robust data model for AAM vertiport flow management, and consolidated this model with layer- and corridor-based ConOps for dynamic structuring of vertiport airspace. An on-demand flight authorisation problem was subsequently addressed using procedural, optimisation and DRL techniques. Numerical experiments demonstrated the correct operation of all approaches, with DRL offering the most scalable and robust solution for vertiport traffic management.

Future work will incorporate more realistic vehicle, battery and environmental models, while exploring the impact of CNS coverage limitations and communication with ATC. Additionally, limited charging bay capacity, uncooperative aerial entities and external AAM traffic will be simulated. The study will also investigate the resilience of the DRL solution to uncertainties and non-deterministic events. Furthermore, hybrid scheduling schemes and collaborative multi-vertiport environments will be considered. Finally, this work will be extended to a multi-agent safe and explainable RL system that optimises resources across multiple transportation domains.

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