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REGULAR PAPER

Towards Planning Urban Air Mobility (UAM) Landing Trajectories in Emergencies

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Abstract

Ground transportation in dense urban environments has been facing challenges for many years (e.g., congestion and resilience) and the problem of congestion in urban environments will become more significant with the growth of populations and urbanization. In the past few years, the industry and the scientific communities have invested resources towards creating new ideas to improve urban transportation performance, such as the Urban Air Mobility (UAM) concept. Therefore, emergencies are considered a pivotal aspect to be managed appropriately to ensure safe UAM operations. Although normal operations represent a challenge nowadays (e.g., performance and social acceptance), emergencies are even more challenging due to the safety-critical risks. Thereupon, the main goal of this research is to propose the Landing Trajectory Planner for Emergencies in UAM Operations (LTPE), using Parallel Metaheuristics and considering autonomous vehicles' presence. This trajectory planning method aims to design landing trajectories for multiple Electrical Vertical Take-off and Landing (eVTOL) vehicles in normal conditions and in emergencies. LTPE considers different eVTOL configurations in piloting systems (i.e., piloted vehicles, remotely piloted vehicles, and fully autonomous vehicles) as well as different vehicle priorities. Three landing modes are used for vehicles in emergency conditions: (i) land at the originally designed skyport; (ii) land at the nearest skyport; and (iii) land on the ground) and all metaheuristics include an early stopping feature. The experiments showed that LTPE can propose safe and efficient solutions for several scenarios with a short response time.

Keywords Urban air mobility · eVTOL · UAS · Artificial intelligence · Evolutionary computing · Trajectory planning · Airspace · Safety

1 Introduction

Ground transportation in dense urban environments has been facing challenges for many years, e.g., congestion and resilience (e.g., the capability of maintaining appropriate workload levels during and after an unexpected increase in airspace complexity). In the past few years, the industry and the scientific communities have invested resources to create new ideas to improve urban transportation performance. An essential outcome of this process is the conception of a smart air transportation system, which composes the Urban Air Mobility (UAM) concept [1–3]. UAM is a transportation concept in which people and goods are moved around metropolitan areas in air vehicles in a diverse airspace environment [4]. There are projects under development and in operation nowadays in the industry in the context of air transportation services in Smart Cities and IoT, such as the Uber Elevate [5], the Amazon Prime Air [6], and NASA's Unmanned Aircraft System (UAS) [7]. These projects aim at enhancing city transportation services using manned and unmanned vehicles. However, there is a concern regarding the usage of such technologies from a safety standpoint. Furthermore, autonomous vehicles bring several benefits to society, such as saving lives, increased mobility, reducing the cost of congestion, reducing energy use and fuel emissions, and improving land use (for ground vehicles) [8]. Conversely, the acceptance of these technologies by society is a challenge nowadays from different perspectives.

Conversely, trajectory planning is not a simple task due to several factors. Firstly, the trajectories must consider a reduced minimum separation as eVTOL vehicles are

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expected to operate in complex urban environments. This leads the trajectory planning process to observe safety primitives more restrictively once the operations are expected to consider many vehicles that follow small minimum separation standards. Also, the distance among the eVTOL vehicles tends to be reduced in the UAM terminal areas, which makes the design of landing trajectories challenging.

Secondly, dense environments tend to be expected in UAM operations. This hardens planning landing trajectories once many deviations from the direct flight tend to be required. These deviations in the optimal trajectory may be challenging to design since the high number of vehicles (and their required minimum separation) reduces the regions in which eVTOL vehicles can fly.

Thirdly, planning emergency UAM operations poses a challenge given the highly constrained environment. This problem becomes even more challenging if multiple eVTOL vehicles declare an emergency and a prioritization process must occur. Furthermore, designing landing trajectories for multiple prioritized eVTOL vehicles (autonomous or manned) is a complex problem due to several factors (e.g., separation criteria). Finally, once the solutions must be provided meanwhile the eVTOL vehicles are operating under an emergency, the reduced response time is essential (i.e., long response times may lead the UAM operation to reach unsafe states). Furthermore, the areas close to the skyports are likely to be the most resource-constrained once the vehicle density tends to be considerably high [9, 10]. Indeed, landing trajectories are challenging since many different vehicles' trajectories must be taken into account in the planning process. Hence, the task becomes more challenging in emergencies.

Finally, the inclusion of Unmanned Aircraft Systems (UAS) [11–13] - also referred to as Autonomous vehicles - in UAM operations is a challenge for many reasons (e.g., social acceptance). To include these vehicles alongside manned vehicles, alternative approaches must be considered (e.g., increased longitudinal separation), which may also harden planning trajectories for other aircraft.

The primary goal of this research is to propose the Landing Trajectory Planner for Emergencies in UAM Operations (LTPE), using Parallel Metaheuristics [14–20] and considering autonomous vehicles' presence. This trajectory planning method aims to design landing trajectories for multiple Electrical Vertical Take-off and Landing (eVTOL) vehicles in normal conditions and emergencies. LTPE considers different eVTOL configurations in piloting systems (i.e., piloted vehicles, remotely piloted vehicles, and fully autonomous vehicles) as well as different vehicle priorities. Three landing modes are used for vehicles in emergency conditions: (i) land at the originally designed skyport; (ii) land at the nearest skyport; and (iii) land on the ground) and all metaheuristics include an early stopping feature. To accomplish this, the proposed approach (i) receives as input the information about the set of eVTOL vehicles (e.g., position, speed, vertical and horizontal separation criteria, and destination) that require a landing trajectory, (ii) sorts the eVTOL vehicles accordingly to their emergency priority, (iii) assigns optimized trajectories to all eVTOL vehicles accordingly to their priorities (i.e., vehicles with higher priorities are more likely to be assigned to higher-quality trajectories), and (iv) exports the solutions at short response times. Therefore, the main contributions of this research are:

- A prioritized trajectory planning method for enabling safe and efficient emergency UAM operations called Landing Trajectory Planner for Emergencies in UAM Operations (LTPE). This approach enables solutions to be efficient and compliant with the operational UAM requirements;
- An extensive performance evaluation of multiple metaheuristics in the optimization of emergency landing procedures. Multiple widely-used techniques are considered with different configurations. This analysis comprises key indicators, e.g., processing time and flight time.
- A comprehensive list of immediate future directions targeting aspects not covered in this investigation. This sheds light on how our contributions can be further extended to address critical issues, e.g., piloting, model boundaries, and other human factors.

In the past few years, the research community has published correlated efforts that address complex issues. The authors in [21] present a framework to perform energy-efficient arrival for multirotor urban eVTOL operations given the required time of arrival (RTA) constraint. In this regard, energy consumption is considered the performance index. Although eVTOL air taxis have the potential to enhance urban transportation, the endurance of Lithium-ion Polymer (Li-Po) batteries imposes a challenging constraint (i.e., the operational time span of an eVTOL vehicle is a challenge to be faced regarding UAM operations). Thus, the proposed contribution enables eVTOL air taxis to comply with the Required Time of Arrival (RTA) and achieve energy-efficient arrival trajectories. Indeed, this is a critical enabler for safe and efficient UAM operations. The numerical experiments showed that shortening the cruise segment and a shallower descent enables better delay absorption for energy-efficient arrival operations. As future directions, the authors highlight that vertical trajectory optimization, trajectory optimization of a tandem tilt-wing eVTOL, and arrival scheduling of multiple eVTOL air taxis are included in their plans. In addition to this, our research is focused on planning landing trajectories in UAM emergencies.

Jin et al. [22] introduce a temporal and spatial routing algorithm and simulation platform for small Unmanned Aircraft System (sUAS) trajectory management in a high-density urban area. Furthermore, this algorithm plans sUAS movements in a spatial and temporal maze, whereas static and dynamic obstacles are avoided. Indeed, sUAS represent an important component of future urban operation and the demand for such vehicles tends to rise. For example, commercial delivery and land surveying are services likely to rely on the use of sUAS. Moreover, traffic routing and management functions are needed for such operations. The coordination of the launching (take-off) of sUAS and trajectories to avoid conflict upon the several considered constraints is a pivotal aspect of enabling safe and efficient operations. Conversely, the growth of airspace density is expected to be even more significant in the next years, and it hardens the process of maintaining safe and efficient operations. The results showed that this algorithm can manage sUAS routes efficiently and with a short response time. Finally, integrating the proposed approach with other simulation tools is highlighted as a future direction of this effort. In addition to this contribution, our focus is on emergencies in UAM operations, which is a complementary contribution. We apply parallel metaheuristics to solve this problem.

Scala et al. [23] propose a methodology for developing an airport arrival and departure manager tool. As optimization and simulation techniques are used to improve the robustness of several airspace tasks, the authors highlight the importance of focusing on arrival and departure challenges. The main goal of this contribution is to help Air Traffic Controllers (ATCo) manage the traffic without incurring conflicts or delays. In fact, this tool can help these professionals to make the right decisions in a short time. This methodology considers each aircraft's features related to entry time and entry speed in the airspace and pushback time at the gate. Finally, this approach presents a smooth flow of aircraft both in the airspace and on the ground. The experiments considered the Paris Charles de Gaulle Airport as the case study. The results showed that conflicts were sensibly reduced. This is a contribution that supports and enhances the current National Airspace System (NAS). In fact, the success of future operations (e.g., UAM) relies on several pillars, including the development of supportive systems. In this sense, our contribution aims to enhance UAM operation in emergencies, which can maintain the system safe even in unexpected conditions.

An approach to noise mitigation that involves both aircraft trajectory and propulsion-airframe design and integration in UAM operations is presented in [24]. In this sense, the trajectories are coupled to an acoustic model that tracks the sound pressure level perceived on the ground. The optimal control is performed using Dymos, which enables optimal control problems to be solved efficiently. This is due to the use of well-defined techniques (e.g., Gauss-Lobatto collocation and Radau Pseudospectral Method). Furthermore, this analysis aimed to measure and ensure that multiple aircraft can operate in densely populated areas without causing excessive noise levels. Throughout the paper, the authors present aspects of the system modeling, the definition of the problem faced, and the results achieved in the experiments. The outcomes (achieved using gradient-based optimization with analytic derivative) showed that trajectories that minimize the total propulsive impulse while respecting limits imposed on the sound pressure level were successfully generated. It is also stated that the most efficient way to respect the constraint relies on altitude gain rather than moving laterally away from the acoustic observer. As future directions of this research, the authors highlight, for example, the development of a realistic source noise model. Finally, this research presents a novel and valuable contribution once it focuses on one important aspect of UAM operation. Thereupon, this effort presents an optimization strategy for increasing the social acceptance of this new transportation system.

The authors in [25] propose an approach to minimize the makespan (landing completion time) of eVTOL vehicles. In fact, this can also be considered as an approach to maximize the arrival throughput. Thus, the main goal of this research is to find the eVTOL aircraft landing order heuristically for a mixed fleet (winged/wingless) that minimizes the makespan of the eVTOLs to land. In this sense, the eVTOL aircraft sequencing and scheduling problem have been formulated in the UAM context for a mixed fleet (winged/wingless) of eVTOL vehicles expected to land on a vertiport with a single landing pad. Furthermore, the authors optimize the landing order and makespan of the mixed fleet using a heuristic approach called Insertion and Local Search (ILS) combined with Mixed-Integer Linear Programming or Time-Advance (TA) algorithm. The experiments showed that the approach proposed is capable of scheduling UAM arrivals in real time. Also, ILS-TA is computationally faster than ILS-MILP, although both produce the same optimal results. Finally, the experiments showed that ILS-TA can schedule 250 eVTOLs in less than 10 seconds. This contribution represents a potential future service for UAM vertiports and supports the increase of UAM performance. In addition to all these contributions, our work proposes a novel method to address a critical issue for eVTOL operations while extensively evaluating the performance of multiple metaheuristics.

This paper is organized as follows: Section 2 introduces the main contribution of this research, the Landing Trajectory Planner for Emergencies in UAM Operations (LTPE), and discusses the problem formulations and assumptions. Secondly, the evaluation method, the scenario building procedure, and the execution method are depicted in Section 3. After that, Section 4 presents the case studies, highlighting the main findings and comparing the results of multiple approaches. Finally, Section 5 presents the conclusion of this research and sheds light on the future research directions.

2 Problem Formulations and Assumptions

The main goal of the Landing Trajectory Planner for Emergencies in UAM Operations (LTPE) is to tactically plan safe and efficient landing trajectories for multiple Electric Vertical Take-off and Landing (eVTOL) vehicles in emergencies. This Decision Support Tool (DST) presents the following features:

- Different configurations in terms of piloting systems are considered (i.e., LTPE considers human-piloted and autonomous - remotely piloted and fully autonomous - vehicles);
- As dealing with single- and multi-emergencies, LTPE considers different priorities for each vehicle in order to identify which vehicles are expected to land first, i.e., to be assigned to the shorter trajectories;
- LTPE uses parallel metaheuristics to quicken the trajectories' design and can provide feasible solutions at a short response time;
- LTPE is compliant with the constraints of UAM operations (e.g., horizontal and vertical separations, eVTOL vehicle specs, flight levels, and landing capability).

In order to accomplish this, LTPE:

- receives as input the information about the set of eVTOL vehicles (e.g., position, speed, vertical and horizontal separation criteria, and destination) that require a landing trajectory;
- orders the eVTOL vehicles according to their emergency priority and departure time;
- assigns optimized trajectories to all eVTOL vehicles according to their order (i.e., vehicles with higher priorities are more likely to be assigned to higher-quality trajectories); and
- exports the solutions at short response times.

2.1 Assumptions

This Section presents the assumptions considered for the appropriate application of LTPE to different problems. Firstly, we present the aspects related to simulation, early stopping, and priorities in emergencies. After that, the aspects of flight levels are depicted. Finally, the response time requirements are shown.

2.1.1 Trajectory-Based UAM Operations Simulator (TUS)

The Trajectory-Based UAM Simulator (TUS) [26] is a simulation platform that evaluates UAM trajectories in urban environments considering both manned and unmanned eVTOL vehicles. The input is composed of the eVTOL vehicles and their specs, separation requirements, origin and destination, and trajectories. The output is composed of the feasibility and the flight time of each trajectory.

TUS is the underlying simulation engine that supports the evaluation of different solutions proposed by LTPE. In fact, this platform enables the evaluation of solutions for different scenarios and constraints (e.g., restricted areas) as well as different aircraft performance. Finally, TUS is an efficient platform that produces solutions in a short response time.

2.1.2 Simulation of Off-Nominal Flight Performance

TUS provides validated flight simulation capabilities. However, this assessment was conducted using Bluesky [27]. This popular Air Traffic Management (ATM) and air traffic flow simulation platform models several scenarios in the National Airspace System (NAS) and provides valuable insights on aircraft performance. However, this tool does not simulate all aspects related to emergencies, e.g., characteristics of engine failures and human factors. Conversely, other emergency factors can be evaluated, e.g., increase in airspace complexity, sequencing optimization, aircraft prioritization, and trajectory and route planning.

Similarly, although TUS presents several modeling features, specific aspects of emergencies are not directly simulated (e.g., human factors and aircraft weight). Hence, adopting TUS in this research enables the development and evaluation of global parameters of emergencies, more specifically trajectories, designated skyport, UAM complexity, and predictability of sequences and priorities. Granular assessments of emergencies (e.g., human factors, physical characteristics of skyports, and dynamic constraints) are pivotal for safe operations and represent the next step of this research.

2.1.3 Priorities in Emergencies

This research adopts five different priorities in UAM operations: 1 (normal operations), 2 (special operations), 3 (very special operations), 4 (urgent operations), and 5 (emergency conditions).

In this sense, LTPE is not designed to measure the priorities of eVTOL vehicles. Rather, it is expected to design safe and efficient arrival trajectories for multiple vehicles, given their priorities. This highlights that the priorities must be provided as input. A method to identify each eVTOL vehicle's priority given its current state is included in the scope of future works.

Although LTPE is designed to produce safe and efficient landing trajectories from multiple eVTOL vehicles in emergencies (considering the short response time requirement), it is also capable of producing safe landing trajectories for normal operations. Indeed, if all vehicles are assigned to priority

1 (i.e., normal operations), LTPE acts as an arrival optimizer for simple (in case there are few vehicles in the airspace) or complex (in case there are several vehicles in the airspace) operations.

2.1.4 Landing Modes

Similarly to the procedures for RPAS [5, 28–30], eVTOL vehicles that declare emergency may (i) land vertically on the ground (i.e., the current vehicle location), (ii) land at the nearest skyport, or (iii) land at the originally assigned skyport. Indeed, these different options might present a significant impact on the UAM operation. Indeed, if the vehicle does not present conditions of completing the initial flight plan, it must land at its earliest convenience.

Similarly to the National Airspace System (NAS), it is reasonable to consider that pilots (human or not) determine the best strategy for a safe landing procedure and interact with the ATC to enable such an approach. Defining the best approach to be followed is a complex task that depends on several factors (e.g., ground restrictions, airspace complexity, and eVTOL vehicle autonomy).

However, similarly to what happens in the Nation Airspace System (NAS) with deviations [10], these maneuvers may present a considerable impact in the UAM operations. In case the eVTOL vehicle needs to land on the ground, it may compromise the safety of people in streets, railways, and buildings. The Air Traffic Control (ATC) must elaborate a strategy to conduct this vehicle to a skyport when flying again. Furthermore, this might also affect the social acceptance of UAM operations once such procedures may compromise public safety.

On the other hand, if the eVTOL vehicle is assigned to land at the nearest skyport, it can present an impact on the skyport (since the capacity and operational planning might suffer a significant change), on several other flights (once crossing trajectories might be created), and on the operational planning of different areas of the airspace (e.g., many flights can be delayed to ensure safe operations).

Regardless of the impacts on the system performance, these strategies must be followed to maintain the airspace safe, whether they are the only safe option available. Conversely, there are many situations in which the vehicles declare an emergency and can still land at the initially defined skyport. Note that the eVTOL vehicle pilot (human or not) is responsible for deciding the landing strategy to be followed [31]. Indeed, those vehicles must be assigned to higher-priority trajectories that reduce their flight time taking into account the airspace constraints.

Thereupon, LTPE considers three landing modes: (i) land vertically on the ground; (ii) land at the nearest skyport; and (iii) land at the original destination skyport. These three landing modes are illustrated in Fig. 1.

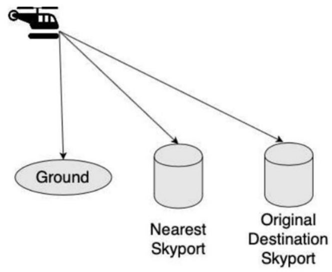


Fig. 1 Landing modes used by LTPE

In this context, the goal of LTPE is to provide safe and efficient landing trajectories considering all the different landing modes. The most appropriate landing mode depends on the scenario faced and is defined by the eVTOL vehicle pilot (human or not). Note that our proposal's focus relies on the design of trajectories, but the selection of the landing mode to be used is an input provided by the user.

2.1.5 Flight Levels

The flight levels considered in this research are 1000ft, 1200ft, 1400ft, and 1600ft. If the vehicle heading throughout the flight is generally less than 180 degrees, the vehicle can operate in levels 1000ft and 1400ft. Otherwise, the operation is conducted at levels 1200ft and 1600ft. Thereupon, LTPE respects this convention and produces trajectories for eVTOL vehicles considering their respective flight levels. Although LTPE does not assign trajectory points in incompatible altitudes, the altitude change procedure (climb or descent) leads the eVTOL vehicles to change their altitude and fly at different altitudes gradually.

In other words, an eVTOL vehicle climbing from 1000ft to 1400ft must cross the 1200ft altitude for a little while. Finally, the vehicles are assigned to a landing fix before starting the actual landing procedure. This fix is located at the lowest eVTOL vehicle level (i.e., 1000ft if the heading throughout the flight is generally is less than 180 degrees or 1200ft otherwise). Future directions of this research can conduct experiments without restrictions regarding altitude.

2.1.6 Response Time Requirements

LTPE is built considering parallel mechanisms to considerably reduce response time to a reasonably short period. The motivation behind this requirement is to enable LTPE to produce feasible solutions efficiently to support operations by using predicted future states, which demands the provision of a safe and efficient solution at a short response time.

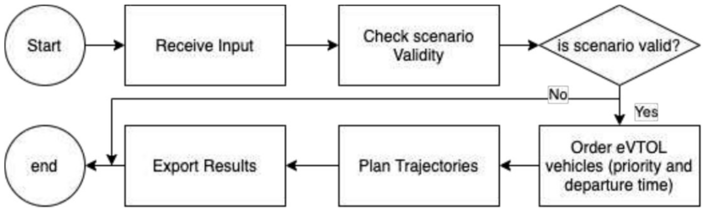


Fig. 2 Flow chart of the Landing Trajectory Planner for Emergencies in UAM Operations (LTPE)

In this sense, similarly to NAS procedures, we consider that a solution is produced at a short response time if it does not compromise the separation criteria of the eVTOL vehicles. In other words, the solutions must be provided within a time interval that does lead the eVTOL vehicle to a Loss of Separation (LoS).

Thereupon, suppose a fleet F with n eVTOL vehicles to be assigned to landing trajectories. In this sense, the response time threshold T_{ev_i} for a specific eVTOL vehicle ev_i ($i = 1, \ldots, n$) is depicted in Eqs. 1 and 2, which are designed by the authors.

$$T_{ev_i} = TTC(ev_i) \times APTP \tag{1}$$

$$TTC(ev_i) = \frac{(D(ev_i, ev_k) - max(HS_{ev_i}, HS_{ev_k}))}{(S_{ev_i} + S_{ev_k})} \times 3600 \tag{2}$$

In these equations, T_{ev_i} represents the response time threshold for designing the landing trajectory for eVTOL vehicles ev_i. T_{ev_i} is the result of the multiplication of two terms. The first component is the Time to Conflict (TTC), which estimates the time (in seconds) that separates ev_i from a conflict. The definition of TTC is presented in Eq. 2. Hence, the closest vehicle to ev_i is referred to as ev_k. $D(e_i, e_k)$ represents the distance (NM) between vehicles ev_i and ev_k. HS_{ev_i} and HS_{ev_k} represent, respectively, the horizontal separation requirements for vehicles ev_i and ev_k (NM). Similarly, S_{ev_i} and S_{ev_k} represent, respectively, the current speed of vehicles ev_i and ev_k (NM). The numerator of this equation computes the distance between these eVTOL vehicles and then discounts the maximum separation requirement between them. This would identify the distance between the conflict of these two vehicles and enable its avoidance. On the other hand, the denominator equals the sum of the current speeds. In this case, the sum of the speeds refers to the analysis of the worst-case scenario (i.e., when the vehicles are flying in opposite directions). Then, the result of this division is multiplied by 3600 to express the time in seconds rather than hours.

The second term of Eq. 1 is the Acceptable Processing Time Percentage (APTP), which varies from 0 to 1 and represents the acceptable percentage of TTC that can be used for designing the trajectories. This value can be configured to different extents. However, we consider $APT = 0.5$ in this research since this represents that only 50% of this time can be used for processing. Note that this value can also be changed to model different time requirements.

Moreover, T_{ev_i} is expressed in seconds and highlights the required response time for designing a single vehicle's trajectory. For all vehicles, the actual response time threshold must cover all the requirements. In order to meet the response time requirements for all eVTOL vehicles, the global threshold T_{global} is considered in the minimum threshold (i.e., the most restrictive threshold), as depicted in Eq. 3.

$$T_{global} = min(T_{ev_1}, T_{ev_2}, ..., T_{ev_n}) \tag{3}$$

Thereupon, we considered response times below T_{global} to be short. In the NAS, radar vectoring can take a couple of seconds as long as it does not compromise airspace safety. Similarly, the same rationale is adopted in UAM operations to identify appropriate response times for different scenarios.

2.2 Aspects of LTPE Implementation

This Section presents the aspects of LTPE implementation. Firstly, the LTPE structure is presented. After that, a discussion on the prioritized ordering procedure is conducted. Finally, the trajectory planning process and the output generation are shown.

2.2.1 LTPE Structure

Figure 2 highlights how LTPE works from a broader standpoint. Firstly, the "Receive Input" phase collects the infor-

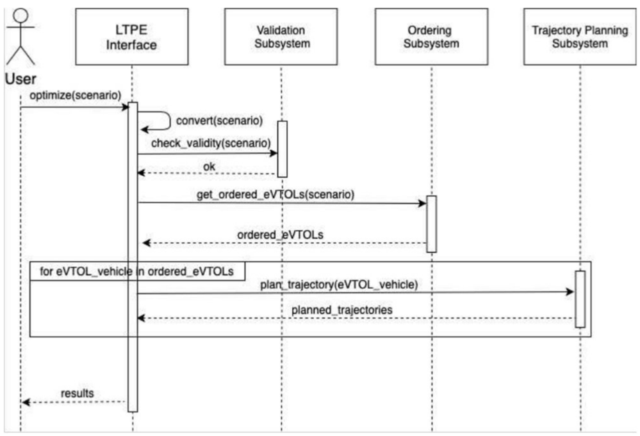


Fig. 3 Sequence Diagram of the Landing Trajectory Planner for Emergencies in UAM Operations (LTPE)

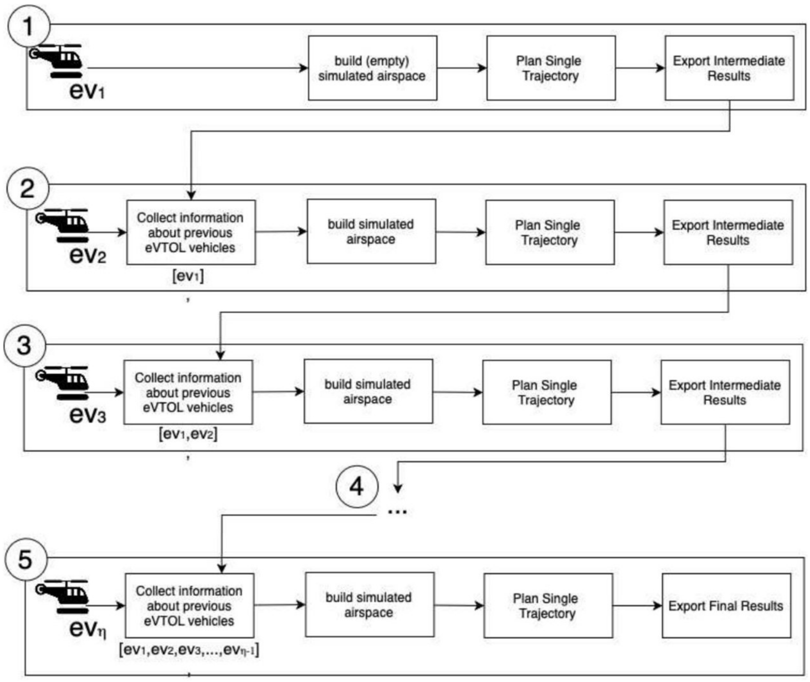


Fig. 4 Trajectory Planning method adopted by LTPE

mation regarding the scenario to be optimized and creates its internal representations. Secondly, the validity of the scenario provided is checked (in a phase named "Check Scenario Validity") to ensure the scenario provided does not start in an unsafe condition. Thirdly, the eVTOL vehicles are ordered by their priorities and departure times. Then, the trajectories are planned sequentially, considering the pre-defined order. Finally, the results are exported.

Moreover, Fig. 3 shows the sequence diagram of LTPE. Firstly, the user interacts with the LTPE interface, asking for a solution for a given scenario. Secondly, the scenario provided as input is converted to the internal scenario's representation (i.e., a group of variables is defined to store the characteristics of the scenario) in memory. Thirdly, the interface is responsible for interacting with the validation subsystem to ensure the scenario provided does not present an unsafe state (i.e., a state with a conflict). If the scenario is valid, the process can continue. Otherwise, the user receives an alert saying the scenario is not valid.

After that, the scenario is provided to the ordering subsystem, which is responsible for defining the order in which the eVTOL vehicles' trajectories will be planned considering (i) their priorities and (ii) their departure times. Finally, each eVTOL vehicle's trajectory is planned and the results achieved are parsed and returned to the user.

2.2.2 Prioritized Ordering and Trajectory Planning

The eVTOL vehicles are assigned to priorities. These priorities vary from 1 (normal operations) up to 5 (emergency conditions) and are used to indicate the order in which the flights should be planned, i.e., a flight with a higher priority is planned before flights with lower priorities. LTPE establishes the order in which flights are planned based on the following criteria: (i) the flight priority[1], and (ii) departure time. Thereupon, flights with higher priorities are planned first, and flights with earlier departure times are planned first in case of equivalent priorities. This strategy respects the urgency of high-priority flights as well as tries to comply with the First-In-First-Out (FIFO) rule.

The first step towards trajectory planning is to define the destination skyport for all eVTOL vehicles. This process considers that all eVTOL vehicles with priorities 1-4 remain with the same destination skyport as provided in the input file.

However, the eVTOL vehicles operating under emergency conditions depend on the landing mode parameter to be assigned to a destination skyport. If the landing mode is set as "original_skyport", those eVTOL vehicles are assigned to their origin skyports, i.e., the skyports defined in the JSON file.

On the other hand, if the landing mode provided is "nearest_skyport", the distance to all available skyports is calculated and the closest skyport is set to be the destination skyport. Finally, if the landing mode is set to "ground", the destination of the eVTOL vehicle is set to be at its current position in the x and y axis, but on the ground.

Figure 4 illustrates the trajectory planning approach adopted in this research. Note that, at this stage, LTPE is expected to have access to an ordered list of eVTOL vehicles and their respective information (e.g., position and speed).

[1] considering 5 as the highest priority and 1 as the lowest priority.

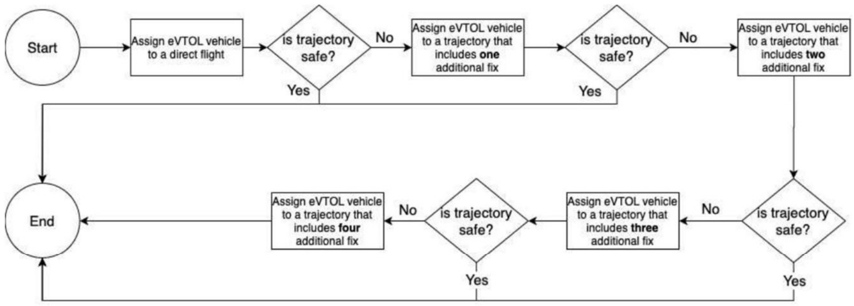


Fig. 5 Process adopted to plan a single trajectory

The approach adopted herein is sequential, i.e., one trajectory is planned at a time.

Firstly, LTPE selects the first eVTOL vehicle ev_1 of the ordered list and considers this is the only vehicle in the airspace. This enables a direct flight and a reduced flight time for the top priority vehicles. A simulated airspace environment without eVTOL vehicles is then built to enable LTPE to plan ev_1's trajectory. After that, this single trajectory is planned (which consists of a direct flight once no conflict is generated). Finally, the results of this single trajectory planning process are exported.

Once the first eVTOL vehicle is assigned to a trajectory, LTPE selects the second eVTOL vehicle ev_2 in the ordered list to go through the same process. However, the simulated airspace environment built at this time is not empty. It includes the presence of all previous eVTOL vehicles that have been assigned to a trajectory (in this case, only ev_1). Note that ev_2 may (or may not) be assigned to a direct flight to its destination depending on compliance with the separation rules considering the pre-defined trajectory for ev_1. At this stage, the trajectory designed for ev_1 does not change. Indeed, the process of designing ev_2's trajectory must consider ev_1's trajectory to avoid conflicts.

This process is repeated to all eVTOL vehicles present in the ordered list, but the number of adjacent vehicles considered in the simulations during the trajectory planning process is incremental (i.e., $[\ ], [ev_1], [ev_1, ev_2], [ev_1, ev_2, ev_3]$ $, ..., [ev_1, ev_2, ev_3, ..., ev_{\eta-1}, ev_\eta]$). One should note that this strategy aims to offer better solutions for prioritized flights by giving them more freedom to fly, whereas lower-priority flights need to be adapted to the airspace considering other pre-planned flights. Finally, note that some defined orders may lead the optimization process to be extremely difficult or unfeasible. Thereupon, if LTPE cannot plan a flight for a given eVTOL vehicle, the entire process of planning trajectories is restarted and the eVTOL vehicles list is randomly shuffled.

Once the airspace simulation model is built and all information needed has been provided, the actual trajectory planning phase can start. Note that single trajectories are planned sequentially, i.e., this is a sequential process in which higher-priority flights are planned first.

Figure 5 illustrates the single trajectory planning process adopted by LTPE. Firstly, the eVTOL vehicle is assigned to a direct flight. The feasibility and effectiveness of this trajectory are then measured by TUS [26], considering other eVTOL vehicles (if there are others). If this solution is feasible (i.e., if the airspace's separations rules are not disrespected), the process is finished and the solution is a direct flight. In summary, this process tests a unique solution that represents a very efficient solution in flight time.

However, if the direct flight does not represent a safe solution, LTPE searches for trajectories (i.e., solutions) that are composed of only one additional fix. This simple strategy is performed once it tends to provide solutions similar to the direct flight, i.e., the eVTOL vehicle tends not to change its operation drastically.

Similarly to the direct flight strategy, the process is finished if a feasible solution is produced. Otherwise, once a feasible solution could not be generated, the entire eVTOL vehicles order is shuffled and the planning process is restarted for all vehicles. This enables LTPE to avoid more complex orders since they are likely to require more processing time (which increases the response time).

Thereupon, if the optimization method cannot find a solution with 4 additional fixes[2], the optimization process for all eVTOL vehicles is restarted and the aforementioned ordered list is shuffled. This is due to the higher optimization difficulty some orders can bring to the problem. Indeed, different orders might require different effort levels for optimization methods. This reinforces the importance of validating if the scenario faced presents feasible solutions.

Moreover, note that a direct fly means that the eVTOL vehicles follow only one fix before landing. This pre-landing fix is located at the same position (x and y) as the destination skyport, at the altitude of the minimum eVTOL vehicle flight level (i.e., 1000ft or 1200ft). Note that this fix has a similar role to the Initial Approach Fix (IAF) in the National Airspace System (NAS).

On the other hand, trajectories that include one or more additional fixes conduct the eVTOL vehicles to different

[2] The limit of 4 fixes is based on the current radar vectoring application in the NAS. However, this limit can be easily extended.

positions before sending them to the pre-landing fix. The optimization process performed by LTPE aims to find appropriate positions (and expected speed of achievement) to efficiently conduct the vehicles. In this sense, each additional fix is composed of (i) a position in the x-axis (i.e., a continuous value), (ii) a position in the y-axis (i.e., a continuous value), (iii) a position in the z-axis (i.e., a discrete value - 1000ft, 1200ft, 1400ft, and 1600ft), and (iv) a speed for the eVTOL vehicle to achieve the position (i.e., a continuous value).

Equation 4k illustrates the objective function considered during the optimization process. In this equation, τ represents the trajectory (i.e., the solution proposed by metaheuristics). Thus, as illustrated in Eq. 5, $\Delta_{e\tau E}$ represents the flight time calculated by TUS given (i) the trajectory τ, (ii) the eVTOL vehicle e, and (iii) the set of the other trajectory-planned eVTOL vehicles E. Thereupon, note that the main goal of the optimization methods is to find a solution (trajectory) τ that reduces the flight time for vehicle e given the previously-designed trajectories for other eVTOL vehicles E. Furthermore, note that if the solution provided is evaluated by TUS as not feasible (i.e., it generates a conflict or leads the vehicle to fly within a restricted area), the value of $\Delta_{e\tau E}$ is considered to be infinity (∞).

$$
\begin{aligned}
&\underset{\tau}{\text{minimize}} \quad f(\tau) = \Delta_{e\tau E} && && \text{(4a)}\\
&\text{subject to} \quad \tau = [x_i, y_i, z_i, s_i] && i = 1, \ldots, d, && \text{(4b)}\\
&sep(e, e', t) \geq \max(e.sep, e'.sep) && \forall e' \in E, \forall t = 0, ..., \Delta_{e\tau E}, && \text{(4c)}\\
&hsep(e, r, t) \geq r.h && \forall r \in R, \forall t = 0, ..., \Delta_{e\tau E}, && \text{(4d)}\\
&x_i \geq x\_lower\_bound && i = 1, \ldots, d, && \text{(4e)}\\
&x_i \leq x\_upper\_bound && i = 1, \ldots, d, && \text{(4f)}\\
&y_i \geq y\_lower\_bound && i = 1, \ldots, d, && \text{(4g)}\\
&y_i \leq y\_upper\_bound && i = 1, \ldots, d, && \text{(4h)}\\
&z_i \in \text{FL} && i = 1, \ldots, d, && \text{(4i)}\\
&s_i \geq speed\_lower\_bound && i = 1, \ldots, d, && \text{(4j)}\\
&s_i \leq top\_speed && i = 1, \ldots, d && \text{(4k)}
\end{aligned}
$$

$$\Delta_{e\tau E} = TUS.simulate(e, \tau, E) \tag{5}$$

The solution τ is composed of 1, 2, 3, or 4 positions. In fact, d represents the number of additional trajectory positions considered in the optimization process[3]. Each position is composed of 4 elements ($[x, y, z, s]$). The values of x and y are expected to vary from a predefined lower and upper bounds range. Finally, the speed s lies in a range of speed lower bound and top speed. Finally, the top speed depends on the eVTOL vehicle performance and it is provided as an input to LTPE. Note that the separation sep of any two eVTOL vehicles e and e' must respect the separation requirements for both of them at any timestamp t. The horizontal distance to a restricted area r must also be respected considering all restricted areas in the airspace (R).

Moreover, a parallel metaheuristic conducts the process of finding feasible solutions. In this research, LTPE considers three different methods: Particle Swarm Optimization (PSO) [32–35], Firefly Algorithm (FA) [36, 37], and Harmony Search (HS) [38–41]. Note that although three widely-used metaheuristics are used herein, different metaheuristics can be used in this research's future directions.

During the optimization process, each decision variable represents the position of the metaheuristic's internal agents in a dimension. These agents can move in high-dimensional space to find regions of high-quality solutions, i.e., to find combinations of decision variables that produce exciting results in terms of flight planning.

The methods as mentioned earlier are implemented in parallel due to the requirement for short response time. In fact, the process illustrated in Fig. 5 is conducted for each single eVTOL vehicle. In this sense, parallel implementations enable a quicker execution of the optimization process.

Furthermore, once a metaheuristic is chosen (and its parameters are set), it is used in each optimization block presented in Fig. 5. Conversely, note that each block requires a new instance of the same metaheuristic once each block considers different numbers of decision variables.

The results exported in each single trajectory planning procedure are composed of (i) the trajectory and (ii) vehicle flight time. The trajectory is composed of a vector of fixes that the eVTOL vehicle must follow. Each component of this vector informs the position (x, y, z) towards which the eVTOL vehicle must fly and the speed (s) at which the eVTOL vehicle must reach that position.

Furthermore, the vehicle flight time represents the duration of the eVTOL vehicle flight from its initial state provided by the user until the end of the landing procedure. This information is relevant to ensure the quality of the solution proposed, i.e., to ensure higher-priority vehicles are assigned to shorter flights throughout the optimization process.

3 Methods

This Section presents the methods adopted in the experiments to show the applicability of the proposed approach to several different airspace configurations. Indeed, these contents are the foundation for the experiments. Firstly, the evaluation method is depicted. Then, the process of generating scenarios and the execution approach are shown.

3.1 Evaluation Method

This evaluation method adopted in this research aims to assess the performance of different LTPE configurations

[3] If the optimization considers one additional position, $d = 1$. If the optimization considers two positions, $d = 2$. If the optimization considers three positions, $d = 3$. Finally, if the optimization considers four positions, $d = 4$.

metaheuristics in solving challenging scenarios. Firstly, the Total Processing Time (TPT) is highlighted. Then, the Processing Earliness Percentage (PEP) is presented. Finally, the Weighted Mean Flight Time (WMFT) is presented.

The Total Processing Time (TPT) refers to the elapsed processing time to design safe and efficient trajectories for all the eVTOL vehicles present in the scenario. Equation 6 highlights how this metric is computed.

$$\epsilon = \sum_{i=1}^{\eta} \epsilon_i \tag{6}$$

This equation highlights that the total processing time (ϵ) is calculated based on the sum of the processing time of designing safe and efficient trajectories for all eVTOL vehicles. The results achieved regarding TPT highlight each metaheuristic's absolute outcome and show how each configuration would perform in different conditions (e.g., different thresholds).

The Processing Earliness Percentage (PEP) refers to each method's capabilities to produce safe and efficient trajectories for all the eVTOL vehicles in a determined time interval (i.e., a specific threshold). In this sense, Eq. 7 shows how this metric is computed.

$$PEP = \frac{T_{global} - TPT}{T_{global}} \tag{7}$$

This equation highlights that, for a given scenario, PEP is the result of the division of the difference between a given global threshold T_{global} and the Total Processing Time (TPT) by T_{global}. This equation gives us the earliness at which the solution is computed in terms of the global threshold (i.e., T_{global}). In other words, in case $T_{global} > TPT$, $PEP > 0$ and $PEP < 1$, whereas in case $T_{global} \leq TPT$, $PEP < 0$. Note that negative values refer to cases in which the threshold was not respected.

The results achieved regarding PEP highlight the relative outcome for each metaheuristic in terms of a specific threshold and show how effectively each configuration is to meet the requirements. Finally, we calculate the required processing threshold as illustrated in Eqs. 1, 2, and 3. This shows the capabilities of the proposed approach. Future works can also consider different thresholds.

Finally, LTPE employs the objective function illustrated in Eq. 4k to optimize single trajectories. However, an evaluation method that computes the solution quality provided from the entire fleet standpoint is also important. Thus, to evaluate the performance of a given solution regarding the trajectory design of the entire fleet, it is important to define an approach that considers the flight times and the priorities of the eVTOL vehicles. In this sense, Eq. 8 presents the Weighted Mean Flight Time (WMFT).

$$wmft = \sum_{i=1}^{\eta} \left(\frac{\rho_i}{\sum_{k=1}^{\eta} \rho_k} \times \Delta_i \right) \tag{8}$$

Given a solution provided by LTPE, η represents the total number of eVTOL vehicles, Δ_i represents the flight time (in seconds) for eVTOL vehicle i when performing the trajectory τ_i, and ρ_i represents the priority for eVTOL vehicle i. Note that ρ_i is divided by $\sum_{k=1}^{\eta} \rho_k$. This associates a weight to each flight time achieved once $\sum_{i=1}^{\eta} \frac{\rho_i}{\sum_{k=1}^{\eta} \rho_k} = 1$. In other words, eVTOL vehicles with higher priorities tend to be more significant in the computation of this mean, whereas eVTOL vehicles with lower priorities tend to be less significant.

Indeed, this highlights that WMFT is more sensitive to the increase in the flight time of higher-priority vehicles rather than lower-priority vehicles. In this sense, the main goal of this metric is to find a weighted mean flight time that assigns more importance to higher-priority vehicles. Note that better solutions (i.e., solutions that present a reduced flight time for higher-priority eVTOL vehicles) reduce this metric's value.

3.2 Scenario Builder

UAM operations are intended to be very dynamic and flexible. This highlights the need for resilience and self-organization. Indeed, the airspace configuration can assume different states and, for example, in severe weather conditions.

Thereupon, these several configurations are generated by various factors (e.g., departure time, trajectory, and Air Traffic Control interventions). An alternative approach to simulate several different scenarios relies on sampling scenarios randomly. Indeed, randomization enables the generation of several scenarios according to a set of constraints.

In this case, the constraints refer to (i) the number of eVTOL vehicles in the local airspace, (ii) the piloting configuration (i.e., if the eVTOL vehicle is piloted - by a human operator-, is an RPAS or a fully automated UAS), (iii) the range (x and y) in which those eVTOLs vehicles can be placed, (iv) their speeds, (v) their current altitude, and (vi) their relative departure time, (vii) their priority, (viii) their destinations, (ix) the restricted areas of the airspace, and (x) their landing mode (if operating under emergency conditions - i.e., if the priority equals 5).

This simple approach enables the generation of multiple scenarios to evaluate this research proposal more accurately. Thus, generating several scenarios enables LTPE to solve various problems that can be faced in UAM operations.

3.2.1 Type-1 Scenario Building

These scenarios present a more challenging task for optimization methods. In this sense, the following aspects are considered:

- 7 eVTOL vehicles are placed between $(x = 0NM, y = 0NM)$ and $(x = 5NM, y = 5NM)$;
- The piloting configuration (i.e., piloted, remotely piloted, and fully autonomous) of each vehicle is defined randomly;
- The top speed of all eVTOL vehicles is set to 170kts with a climb/descent rate of 500ft/min, and turning rate of 7.2 degrees/sec;
- Due to the social acceptance aspect of autonomous platforms, the horizontal and vertical separation requirements for manned eVTOL vehicles are, respectively, 0.25NM and 200ft. The horizontal and vertical separation requirements for unmanned eVTOL vehicles (remotely piloted and fully autonomous) are, respectively, 0.5NM and 200ft [42];
- 3 vehicles are set to be in an emergency condition (i.e., they are set to present 5 as priority) and the others are assigned to a random priority varying from 1 up to 4;
- The vehicles operating under emergency conditions are randomly assigned to a landing mode, i.e., (i) land on the ground, (ii) land at the nearest skyport, or (iii) land at the original skyport destination;
- the eVTOL vehicle initial speed is compatible with the UAM terminal area (i.e., the speeds are randomly set to be $s \in [70, 80]$);
- the current altitudes are represented by random values $z \in [1000, 1200, 1400, 1600]$;
- 4 skyports are randomly placed between $(x = 0NM, y = 0NM)$ and $(x = 5NM, y = 5NM)$;
- The eVTOL vehicles can be horizontally placed at different ranges away from one another if they operate at the same flight level;
- The eVTOL vehicles are randomly assigned to 4 skyport as their destination (i.e., 7 eVTOL vehicles land at 4 skyports), all located at 100ft in the z-axis;
- 2 restricted areas of radius $r = 0.2NM$ are set in the airspace between $(x = 0NM, y = 0NM)$ and $(x = 5NM, y = 5NM)$.

3.2.2 Type-2 Scenario Building

In terms of building these complex scenarios, the following approach is considered:

- 10 eVTOL vehicles are placed between $(x = 0NM, y = 0NM)$ and $(x = 5NM, y = 5NM)$;
- The piloting configuration (i.e., piloted, remotely piloted, and fully autonomous) of each vehicle is defined randomly;
- The top speed of all eVTOL vehicles is set to 170kts with a climb/descent rate of 500ft/min, and turning rate of 7.2 degrees/sec;
- Due to the social acceptance aspect of autonomous platforms, the horizontal and vertical separation requirements for manned eVTOL vehicles are, respectively, 0.25NM and 200ft. The horizontal and vertical separation requirements for unmanned eVTOL vehicles (remotely piloted and fully autonomous) are, respectively, 0.5NM and 200ft [42];
- 4 vehicles are set to be in an emergency condition (i.e., they are set to present 5 as priority) and the others are assigned to a random priority varying from 1 up to 4;
- The vehicles operating under emergency conditions are randomly assigned to a landing mode, i.e., (i) land on the ground, (ii) land at the nearest skyport, or (iii) land at the original skyport destination;
- the eVTOL vehicle initial speed is compatible with the UAM terminal area (i.e., the speeds are randomly set to be $s \in [70, 80]$);
- the current altitudes are represented by random values $z \in [1000, 1200, 1400, 1600]$;
- 5 skyports are randomly placed between $(x = 0NM, y = 0NM)$ and $(x = 5NM, y = 5NM)$;
- The eVTOL vehicles can be horizontally placed at different ranges away from one another if they operate at the same flight level;
- The eVTOL vehicles are randomly assigned to 5 skyports as their destination (i.e., 10 eVTOL vehicles land at 5 skyports), all located at 100ft in the z-axis;
- 2 restricted areas of radius $r = 0.2NM$ are set in the airspace between $(x = 0NM, y = 0NM)$ and $(x = 5NM, y = 5NM)$.

3.3 Execution Method

Once the metrics for evaluating the outcomes achieved and the models for building several scenarios (with different complexity levels) are defined, a complementary but key method to be presented is the execution method.

The main goal of this method is to highlight how scenarios could be generated, parsed, optimized, and how the evaluation of the performance of different metaheuristics could be executed. Figure 6 illustrates the execution method adopted in this research.

Firstly, the generation of different scenarios is performed. This step refers to the application of the scenario-building strategies and enables the test of LTPE at scale. Please note that this step also includes the validation of the scenarios

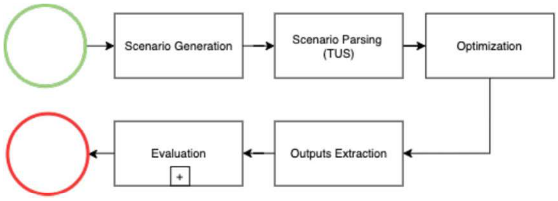


Fig. 6 Execution method adopted in this research

generated. The output of this step is a collection of all information regarding the generated airspace state, which can be of different types.

Secondly, the stage named "Scenario parsing (TUS)" relies on collecting the information generated and using it as an input for the simulation model utilized and proposed in this research. This process enables TUS to use the generated information for building internal representations of the airspace.

Then, step "Optimization" considers the optimization of the pre-generated scenarios. At this state, LTPE is executed using several parallel metaheuristics with different configurations (i.e., Particles Swarm Optimization - PSO -, Firefly Algorithm - FA -, and Harmony Search - HS). In this sense, TUS is used by LTPE during the optimization process to evaluate the solutions produced. Then, the output of each execution is collected. After that, the process of output extraction is performed. This step refers to the extraction of the selected metrics investigated in this research, presented in Section 3.1.

Finally, the evaluation of the performance of all metaheuristics for several scenarios is performed. The details on how the evaluation is executed are depicted in Fig. 7. Firstly, the Total Processing Time (TPT) evaluation is performed, followed by the evaluation of the Processing Earliness Percentage (PEP). Then, the Weighted Mean Flight Time (WMFT) is computed for all scenarios.

Once these values are calculated, the different metaheuristics are filtered. This filtering process is based on the ability of each metaheuristic to produce safe and efficient solutions in the required time interval. In other words, this process selects the configurations that meet the temporal requirements.

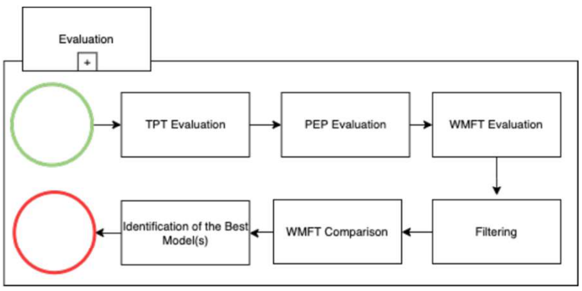


Fig. 7 Details of the evaluation process

After that, we compare the WMFT of all filtered methods, considering the population's characteristics rather than the sample. To accomplish this, we perform a statistical test to verify if the median WMFT for all metaheuristics is statistically different or not. If only two methods are compared, the Mann-Whitney test [43] is used to check if there is a statistically significant difference between them. If three or more methods are compared and the WMFTs computed are normally distributed, we apply the Analysis of Variance (ANOVA) test [44], which tests the null hypothesis that "the groups present the same population mean". Conversely, if three or more methods are compared and the WMFTs computed are not normally distributed, we apply the Kruskal-Wallis test [45], which tests the null hypothesis that "the groups present the same population median". Finally, the D'Agostino and Pearson's normality test [46, 47] is used to check is the groups are normally distributed, which tests the null hypothesis that "a sample comes from a normal distribution". Note that all the tests' results are evaluated with a confidence level of 95%, i.e., $\alpha = 0.05$.

The tests' results highlight the similarities of the results achieved by different optimization approaches. In other words, it shows if all configurations present similar outcomes at scale. Finally, the configuration that presents the best outcomes in the experiments is considered the best solution.

4 Case Studies

This Section presents the experiments conducted in this research. The goals of all experiments are (i) to show the applicability of the proposed strategy in several scenarios and (ii) to compare the outcomes of the Landing Trajectory Planner for Emergencies in UAM Operations (LTPE) considering the use of different metaheuristics.

To accomplish this, Table 1 shows the LTPE configurations used in the experiments. In summary, 12 different LTPE configurations are considered. Note that they also share values of parameters, and their difference lies in the number of particles and Early Stopping (ES) activation. Indeed, there are several research opportunities to find the best parameter arrangement for each metaheuristic, which are in the scope of the future directions of this research.

The PSO is set to have $c_1 = 1$, $c_2 = 1$, and $w = 0.5$. These values are assigned once they comply with the interval adopted in the search process (i.e., these values do not diverge significantly from the search boundaries used - 5NM). Hence, they make the process more dependent on the interaction among the particles. The FA is set to have $\beta_0 = 1$ and $\gamma = 1$. This follows the same principle of PSO, i.e., these values tend to lead the particles to an appropriate distance, given the search bounds. Finally, HS is set to have $r_{pa} = 0.5$, $r_{accept} =$

Table 1 LTPE configurations used in the experiments

id	Metaheuristic	ES	parameters
$P8$	PSO	X	p=8,i=16,c_1=1,c_2=1,w=0.5
$P8E$	PSO	✓	p=8,i=16,c_1=1,c_2=1,w=0.5
$P16$	PSO	X	p=16,i=16,c_1=1,c_2=1,w=0.5
$P16E$	PSO	✓	p=16,i=16,c_1=1,c_2=1,w=0.5
$F8$	FA	X	p=8,i=16,$\beta_0 = 1$,$\gamma = 1$
$F8E$	FA	✓	p=8,i=16,$\beta_0 = 1$,$\gamma = 1$
$F16$	FA	X	p=16,i=16,$\beta_0 = 1$,$\gamma = 1$
$F16E$	FA	✓	p=16,i=16,$\beta_0 = 1$,$\gamma = 1$
$H8$	HS	X	p=8,i=16,r_{pa}=0.5,r_{accept}=0.5,b_{range}=0.5
$H8E$	HS	✓	p=8,i=16,r_{pa}=0.5,r_{accept}=0.5,b_{range}=0.5
$H16$	HS	X	p=16,i=16,r_{pa}=0.5,r_{accept}=0.5,b_{range}=0.5
$H16E$	HS	✓	p=16,i=16,r_{pa}=0.5,r_{accept}=0.5,b_{range}=0.5

0.5, and $b_{range} = 0.5$. This strategy is slightly different once these values refer to probabilities. Thereupon, the idea is to give the same importance to each parameter. Finally, note that the number of particles and iterations is reduced due to the requirement for a short-time response. Indeed, increasing the number of particles and iterations tends to improve the quality of the solutions proposed but, on the other hand, also tends to increase the response time. Finally, note that some models employ Early Stopping (ES).

In this research, we consider a large search space in which $-10 \leq x \leq 15$ and $-10 \leq y \leq 15$. This enables the algorithms to find different solutions with more freedom. The altitude (z) is constrained among the available Flight Levels (FL), i.e., 1000ft and 1400ft, or 1200ft and 1600ft

In Case Study I, these 12 methods are executed to solve 120 type-1 scenarios considering three landing modes for vehicles operating under emergency conditions. In this sense, we vary the vehicles' distances in the initial placement of the eVTOL vehicles - 60 scenarios consider an initial distance of 1.0NM, and another 60 scenarios consider 1.1NM. Similarly, Case Study II focuses on the solution of 120 type-2 scenarios in which we have 60 executions for each placement distance requirement among the vehicles (i.e., 60 for 1.0NM and 60 for 1.1NM). Note that 2880[4] LTPE executions are performed in total once there are 12 models, 120 type-1 scenarios, and 120 type-2 scenarios [48]. Finally, the experiments are performed in a server with 16 vCPUs and 60GB of RAM.

[4] The number of experiments for each configuration was 60 due to different reasons: (i) it is twice as much as the size considered reasonable by many authors (i.e., $n = 30$) [48]; (ii) it enables the hypothesis test application [44, 45, 49]; and (iii) the total number of experiments is large (2880) and shows the capability of the proposed approach in randomly generated scenarios. This shows a balance between processing time and number of experiments performed.

4.1 Case Study I

The main goal of this Case Study is to show the applicability of the proposed strategy in type-1 scenarios. Thus, the experiments considered 180 randomly generated scenarios composed of 7 eVTOL vehicles (with random priorities and current state) that need to be assigned to 5 different skyports. Also, 2 restricted areas are included. The area considered is $5NM \times 5NM$.

4.1.1 Initial Distance of 1.0NM

In this experiment, we optimize 60 type-1 scenarios in which the initial positions of all eVTOL vehicles are at least 1.0NM away from one another.

All metaheuristics are used to solve the 60 scenarios built. In all cases, LTPE was able to produce safe and efficient solutions. Although the metaheuristics vary in terms of WMFT and TPT, all of them can produce feasible solutions.

Figure 8 illustrates the processing threshold of all scenarios. Note that most of these scenarios require less than 10 seconds to be solved. A few values above 25 seconds are also

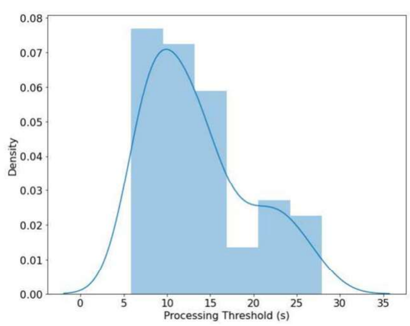


Fig. 8 Processing thresholds for Case Study I (1.0NM of initial distance)

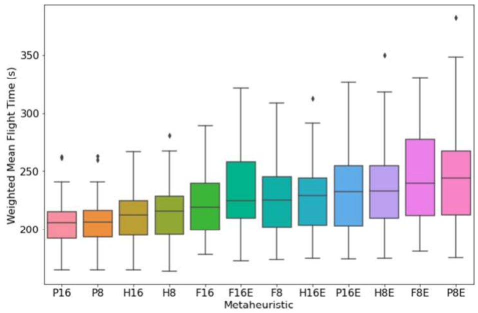


Fig. 9 Comparison of Weighted Mean Flight Time (WMFT) of across metaheuristics in Case Study I (1.0NM of initial distance)

present since the initial state of the airspace has the eVTOL vehicles far from each other in those cases.

Figures 9 and 10 show the performance of all metaheuristics in terms of WMFT (s). Also, Fig. 11 presents the normalized WMFT based on the maximum flight time achieved. In this case, fewer outliers occur. Note that the medians are considerably close to each other.

Moreover, Fig. 12 shows the TPT for all metaheuristics to calculate the solutions. Similarly to the other cases, there is a considerable difference across the metaheuristics.

Figure 13 shows the Processing Earliness Percetage (PEP) for all metaheuristics. The red line indicates the threshold. The positive values highlight cases in which the temporal requirements are met, whereas negative values represent cases in which temporal requirements are not met.

Based on the results illustrated in Fig. 13, metaheuristics can be filtered, and those that meet the temporal requirements can be analyzed. In this particular case, the filtered models are P8E, P16E, HE, H16E, F8E, and F16E.

To identify if the difference in the median outcomes of those methods regarding WMFT is statistically significant, we need to perform the normality test. The outcomes of this test highlighted that P8E, P16E, F8E, F16E, and H8E do not present a normally distributed WMFT (as illustrated in Fig. 10).

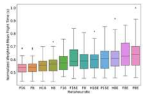


Fig. 11 Comparison normalized WMFT across all metaheuristics in Case Study I (1.0NM of initial distance)

As the data does not follow a normal distribution, we need to use the Kruskal-Wallis method to compare their median. The Kruskal-Wallis method's null hypothesis is that "the groups present the same population median" and we obtained a p-value of 0.057 (which is greater than α - 0.05). This means that the medians are not different with a statistical significance.

In terms of landing mode, as we adopt 60 type-1 scenarios, the vehicles that declared an emergency (i.e., 3 eVTOLs) are randomly assigned to different destinations. Hence, multiple combinations are dealt with in the generation of experimental scenarios. Finally, all filtered metaheuristics performed similarly well regarding WMFT. H16E outperformed the other metaheuristics in the experiments performed and presented 227.16 seconds of mean WMFT and 2.08 of mean TPT.

4.1.2 Initial Distance of 1.1NM

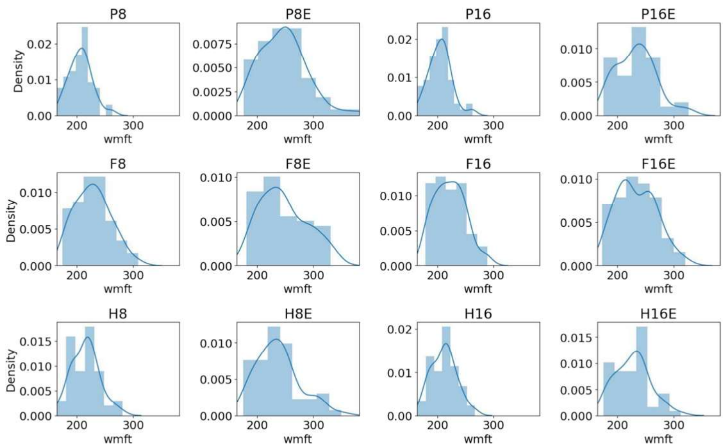
We optimize 60 type-1 scenarios in this experiment considering the initial position of all eVTOL vehicles to be at least 1.1NM away from one another.

In this Section, 60 experiments are performed for each metaheuristic. Similarly to the other experiments, all challenges posed were successfully solved by LTPE, which highlights the capabilities of the proposed approach.

Figure 14 illustrates the processing threshold of all scenarios. In this particular case, most of these scenarios require about 10 seconds to be solved. A few values above 20 seconds are also present since the initial state of the airspace has the eVTOL vehicles far from each other in those cases.

In terms of fitness, Figs. 15 and 16 illustrate the performance of all metaheuristics (WMFT), while Fig. 17 normalizes the overall performance using the maximum flight time achieved. Note that the number of outliers is considerably reduced in these scenarios.

Fig. 10 Weighted Mean Flight Time (WMFT) across all metaheuristics in Case Study I (1.0NM of initial distance)



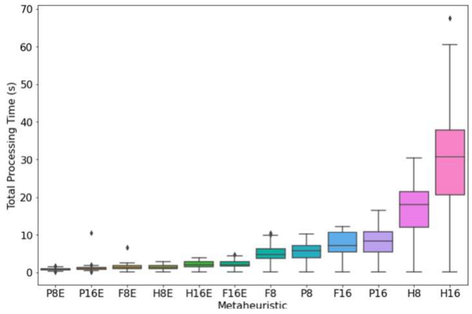


Fig. 12 Total Processing Time (TPT) for Case Study I (1.0NM of initial distance)

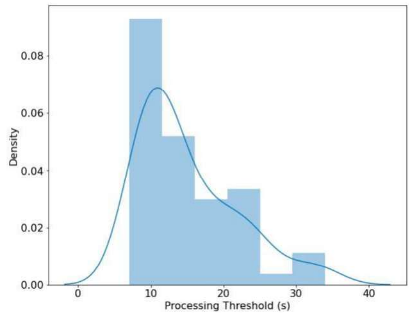


Fig. 14 Processing thresholds for Case Study I (1.1NM of initial distance)

Furthermore, Fig. 18 shows the TPT for all metaheuristics to calculate the solutions. Note that H16 presents a higher TPT in comparison to any other metaheuristic.

Figure 19 simplifies the visualization of the processing time in terms of the threshold. The red line indicates the threshold. The positive values highlight cases in which the temporal requirements are met, whereas negative values represent cases in which temporal requirements are not met.

Based on the results illustrated in Fig. 19, we can filter the metaheuristics to analyze those that met the temporal requirements. In this particular case, the filtered models are P8E, P16E, H8E, H16E, F8E, and F16E.

To identify if the difference in the median outcomes of those methods regarding WMFT is statistically significant, we need to perform the normality test. The outcomes of this test highlighted that P8E does not present a normally distributed WMFT (as illustrated in Fig. 16).

As the data does not follow a normal distribution, we need to use the Kruskal-Wallis method to compare their median. The Kruskal-Wallis method's null hypothesis is that "the groups present the same population median" and we obtained a p-value of 0.04903. Although it is very close to α (0.05), it is still less than α. This means that the medians are different from a statistical significance.

The generation of 60 type-1 scenarios establishes a rich combination of landing models randomly assigned to the 3 eVTOL vehicles that declare emergency. Finally, all filtered metaheuristics performed well regarding WMFT and the best metaheuristic is H16E, which computed feasible solutions with 233.37 seconds of mean WMFT and 2.32 seconds of mean TPT.

4.2 Case Study II

The main goal of this Case Study is to show the applicability of the proposed strategy in type-2 scenarios. The experiments considered 180 randomly generated scenarios composed of 10 eVTOL vehicles (with random priorities and current state) that need to be assigned to 5 different skyports. Also, 2 restricted areas are included. The area considered is $5NM \times 5NM$.

4.2.1 Initial Distance of 1.0NM

In this experiment, we optimize 60 type-2 scenarios in which the initial positions of all eVTOL vehicles are at least 1.0NM away from one another.

We performed 60 experiments for each metaheuristic to evaluate the capability of LTPE in solving these challenges. In this sense, LTPE was able to solve all scenarios faced.

The processing thresholds of all scenarios are illustrated in Fig. 20. Note that all scenarios require less than 20 seconds

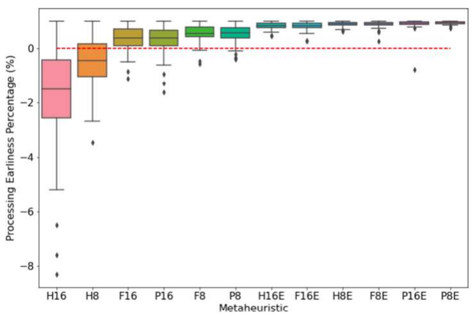


Fig. 13 Processing Earliness Percentage (PEP) for Case Study I (1.0NM of initial distance)

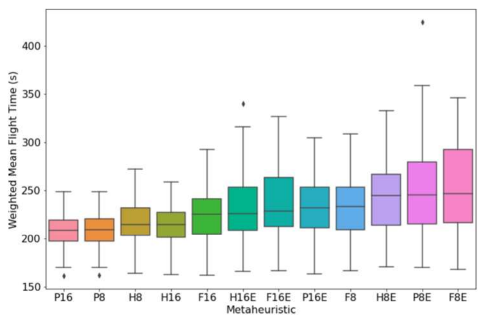


Fig. 15 Comparison among Weighted Mean Flight Time (WMFT) for all metaheuristics in Case Study I (1.1NM of initial distance)

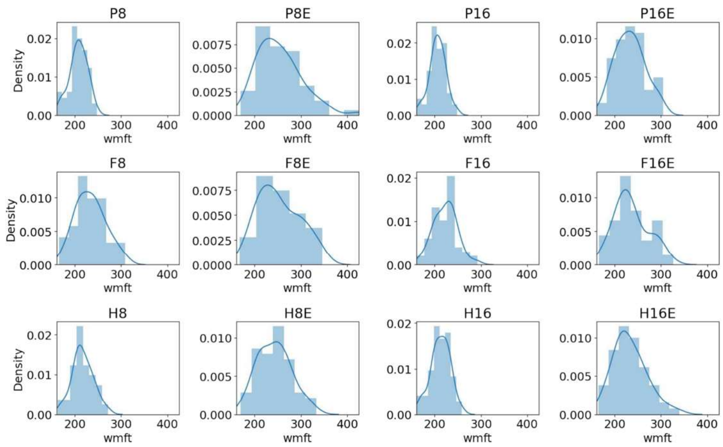


Fig. 16 Weighted Mean Flight Time (WMFT) for all metaheuristics in Case Study I (1.1NM of initial distance)

be get the solution, and most of them require less than 10 seconds. This highlights the complexity of all the 60 scenarios faced.

Figures 21 and 22 depict the outcomes achieved by all metaheuristics in terms of the WMFT (s). In this case, the variation of WMFTs across all metaheuristics is easier to note than in the previous experiments. Figure 23 illustrates the normalized flight performance based on the maximum flight time achieved.

LTPE can solve all cases and provide feasible solutions. Regarding its performance, different metaheuristics bring different outcomes. Figure 24 shows the Total Processing Time (TPT) for each metaheuristic. The trends discovered in the past experiments are also depicted here - H16 presents a higher TPT.

Finally, Fig. 25 presents the Processing Earliness Percentage (PEP). The red line indicates the threshold. The appropriate models to be used when the threshold is considered present all values above the red line.

In this experiment, only P8E, P16E, and F8E presented all values above the red line (Fig. 25). Once these models are the target of this investigation, we perform the normality test. The outcomes of this test highlighted that all these models do not present a normally distributed WMFT (as illustrated in Fig. 22).

Regarding landing modes, the 60 type-2 scenarios generated randomly assign the destination (i.e., land on the ground, land at the nearest skyport, or land at the designated skyport) to the 4 eVTOL in an emergency operation. Also, as the data is not drawn from a normal distribution, we need to use the Kruskal-Wallis method to compare their median. In this test, we obtained a p-value of 0.016. This means that the medians are different from a statistical significance. Finally, the metaheuristic selected as the best due to its reduced mean WMFT (i.e., 247.56 seconds) is the P16E. In terms of mean TPT, P16E spent an average of 2.1 seconds computing the solutions.

4.2.2 Initial Distance of 1.1NM

We optimize 60 type-2 scenarios in this experiment considering the initial positions of all eVTOL vehicles to be at least 1.1NM away from one another.

Figure 26 illustrates the processing threshold of all scenarios - which were successfully solved by LTPE. In this case, most of the values are less than 20 seconds.

Some variability can also be perceived in the performance of the solutions as illustrated in Figs. 27 and 28. Some outliers

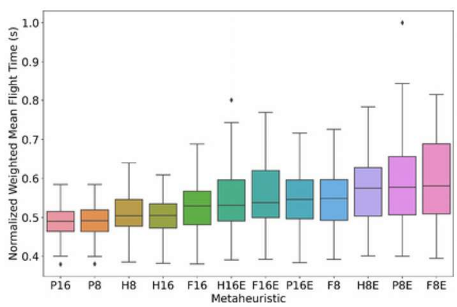


Fig. 17 Comparison normalized WMFT across all metaheuristics in Case Study I (1.1NM of initial distance)

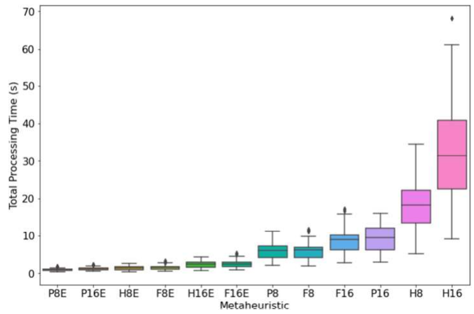


Fig. 18 Total Processing Time (TPT) for Case Study I (1.1NM of initial distance)

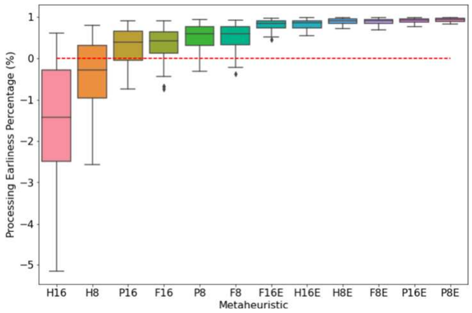


Fig. 19 Processing Earliness Percentage (PEP) for Case Study I (1.1NM of initial distance)

are also presented, including in the normalized plot presented in Fig. 29.

Regarding TPT, Fig. 30 shows the performance of all metaheuristics. In this case, the difference in mean TPT between the best and the worst models is expressive.

This is also reflected in the analysis of the threshold presented in Fig. 31. Note that in all cases, H16 presented PEPs below the threshold line. On the other hand, some models presented all outcomes above the red line.

Based on the results illustrated in Fig. 31, the metaheuristics can be analyzed and filtered in terms of the temporal requirements. In this particular case, the filtered models are P8E, P16E, H8E, and H16E.

To verify whether the difference in the median outcomes of those methods regarding WMFT is statistically significant, we need to perform the normality test. The outcomes of this test highlighted that all metaheuristics do not present a normally distributed WMFT (as illustrated in Fig. 28).

In this case, we need to use the Kruskal-Wallis method to compare their median. The Kruskal-Wallis method's null hypothesis is that "the groups present the same population median" and we obtained a p-value of 0.016. This means that the medians are different from a statistical significance. H16E presented the best outputs across all the selected metaheuristics (i.e., 242.41 seconds of WMFT) at a short response time (i.e., 4.24 seconds of mean TPT). The randomness in the assignment of landing modes to eVTOLs in an emergency enables the experiments to explore multiple combinations, given that 60 scenarios are created.

The numerical results obtained in all experiments are depicted in Table 2. Therefore, the metaheuristics adopted were able to successfully address the issues faced. Finally, some recent works also focussed on trajectory planning for eVTOLs. For example, the authors in [50] propose an autonomous pre-flight and in-flight contingency planning system, but do not consider metaheuristics in their experiments. Similarly, the authors in [51] introduce a trajectory generator and collision avoidance solution for eVTOLs while not focussing on the specific problems addressed in our research. Furthermore, Ye et al. [52] adopt the A* algorithm for eVTOL air route network planning. In addition to these solutions designed to address critical issues to enable safe eVTOL operations, our effort consists of a vital component of emergency operations, employing advanced metaheuristics capable of handling several constraints to generate efficient solutions. The results achieved demonstrate the efficacy of our proposal while comparing the performance of multiple algorithms.

5 Conclusion

This paper presented the Landing Trajectory Planner for Emergencies in UAM Operations (LTPE), using Parallel Metaheuristics and considering the presence of autonomous vehicles. The operations considered are based on multiple Electrical Vertical Take-off and Landing (eVTOL) vehicles in normal conditions and emergencies. Thus, eVTOL vehicle configurations, priorities, specifications, and landing modes were considered. Three landing modes are adopted: (i) land at the originally designed skyport; (ii) land at the nearest skyport; and (iii) land on the ground). Regarding the opti-

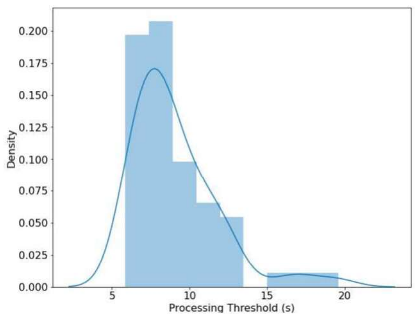


Fig. 20 Processing thresholds for Case Study II (1.0NM of initial distance)

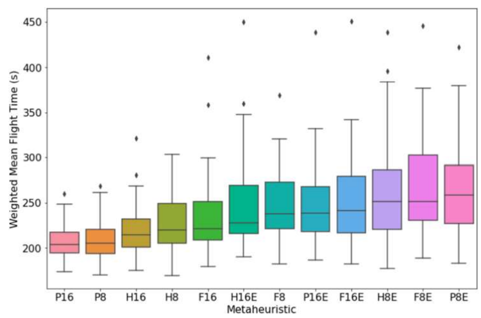


Fig. 21 Comparison of Weighted Mean Flight Time (WMFT) across all metaheuristics in Case Study II (1.0NM of initial distance)

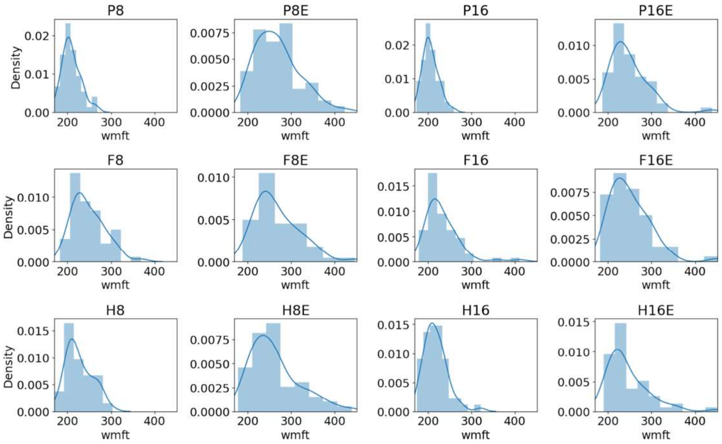


Fig. 22 Weighted Mean Flight Time (WMFT) for all metaheuristics in Case Study II (1.0NM of initial distance)

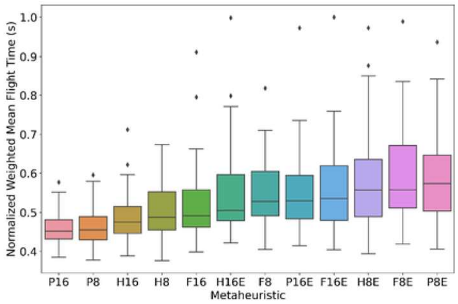


Fig. 23 Comparison normalized WMFT across all metaheuristics in Case Study II (1.0NM of initial distance)

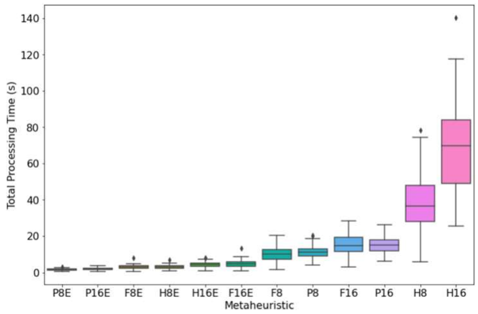


Fig. 24 Total Processing Time (TPT) for Case Study II (1.0NM of initial distance)

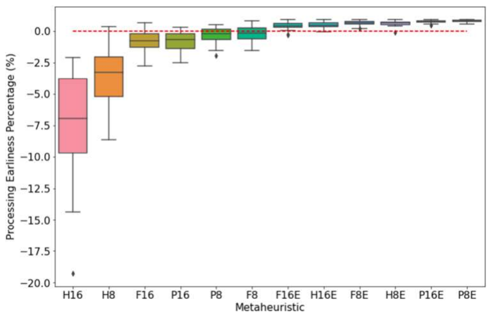


Fig. 25 Processing Earliness Percentage (PEP) for Case Study II (1.0NM of initial distance)

mization process, supporting features are also included (e.g., Early Stopping - ES).

Furthermore, several experiments were performed in a structured way, and the details of each scenario were also highlighted (e.g., the configuration of each scenario type). In total, 4320 experiments were performed considering 60 executions for each combination of scenario types (3), different initial distances (3), and different configurations of LTPE (12).

The results showed that LTPE can provide safe and efficient solutions for all cases investigated. Regardless of the LTPE configuration adopted, feasible solutions were produced. Many configurations were also capable of producing those solutions in a minimal response time. In our experiments, PSO presented the best results in most cases.

Finally, although this work addresses specific topics regarding the UAM operations, there are many possibilities to extend this effort. Some future directions are:

- **Aspects of piloting and their differences:** This direction refers to the in-depth investigation of the differences between manned and unmanned aircraft regarding piloting from different perspectives (e.g., aspects of social acceptance, response time, flight management, and interoperability with other UAM stakeholders);

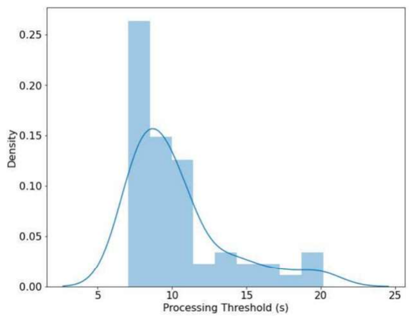


Fig. 26 Processing thresholds for Case Study II (1.1NM of initial distance)

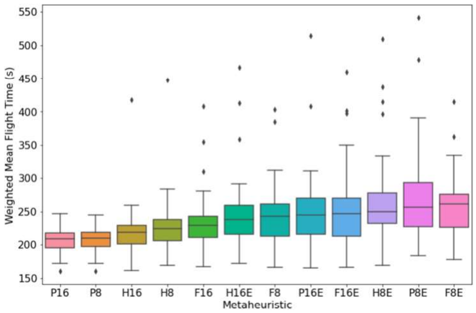
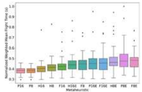


Fig. 27 Comparison of Weighted Mean Flight Time (WMFT) for all metaheuristics in Case Study II (1.1NM of initial distance)

- **Security x Safety:** One interesting direction refers to the impact of security on the safety aspects of UAM operations. This refers to the investigation of several aspects (e.g., data exchange assurance and redundancy);
- **Analysis of the model boundaries:** In this research, we demonstrated that LTPE is capable of solving different realistic scenarios. We also considered different initial separations and complexity levels. Furthermore, a possible future direction relies on the investigation of the limits of LTPE, i.e., future works can investigate which extreme values (e.g., vertical and horizontal separations) can be adopted without compromising the feasibility of the solutions produced;
- **Interaction, communication, and surveillance of the fleet:** Regarding communication, several challenges can be highlighted to be solved in future works. For instance, the development of UAM-enabled networking devices, communication protocols, communication applications, optimization based on Software-Defined Networking (SDN), virtualization, data transmission, and networking metrics (e.g., delay and packet loss);
- **Decision regarding landing mode:** Another interesting future direction relies on the automatic specification of which landing mode to use based on the current UAM airspace state;

Fig. 29 Comparison normalized WMFT across all metaheuristics in Case Study II (1.1NM of initial distance)



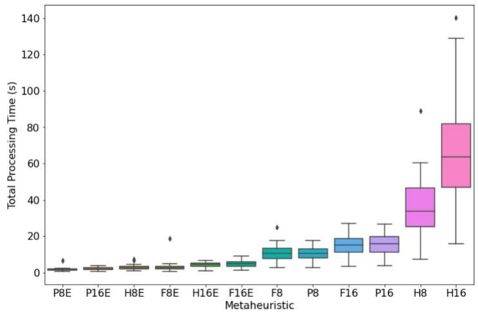


Fig. 30 Total Processing Time (TPT) for Case Study II (1.1NM of initial distance)

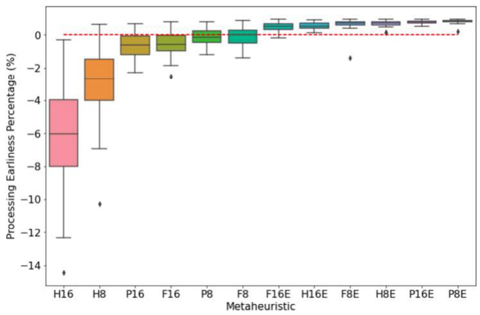


Fig. 31 Processing Earliness Percentage (PEP) for Case Study II (1.1NM of initial distance)

- **Unexpected issues in UAM operations:** The resilience of UAM operations is also included in the scope of future works. This would include failures in communication, problems with the skyports, capacity limitations, and dynamic restrictions.

Fig. 28 Weighted Mean Flight Time (WMFT) for all metaheuristics in Case Study II (1.1NM of initial distance)

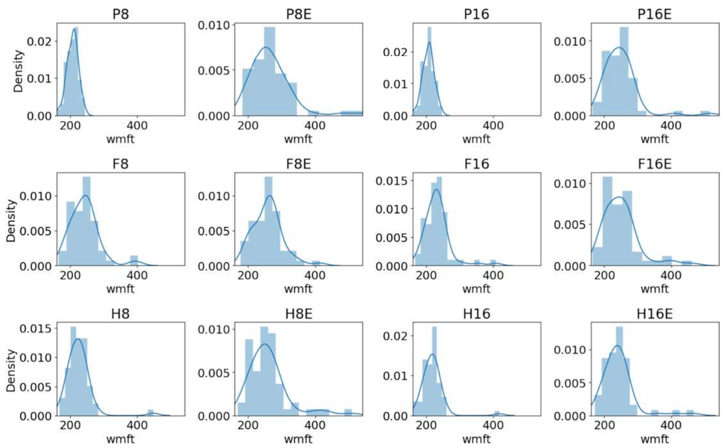


Table 2 WMFT results obtained in all experiments

	Metaheuristic	mean	std	min	25%	50%	75%	max
	PSO-8	206.400	20.592	165.167	193.483	206.914	216.763	262.690
	PSO-8-ES	246.220	41.523	176.000	212.490	243.903	267.731	382.241
	PSO-16	205.091	19.884	165.167	192.392	205.997	215.546	262.517
	PSO-16-ES	232.909	35.159	174.875	203.168	232.429	254.785	326.586
	FA-8	228.174	31.662	173.864	202.288	225.176	245.260	308.862
	FA-8-ES	247.570	41.829	181.259	212.234	239.815	277.691	331.043
	FA-16	222.203	27.376	178.727	199.454	219.610	239.619	289.241
	FA-16-ES	233.647	35.209	173.000	210.147	224.720	257.948	321.241
	HS-8	215.261	24.673	164.167	195.372	216.244	228.995	281.379
	HS-8-ES	237.061	38.435	175.167	209.930	233.070	254.392	350.160
	HS-16	211.728	22.505	165.125	195.063	212.969	224.991	267.240
Case Study I (10 NM)	HS-16-ES	227.163	31.059	175.136	204.110	229.507	244.080	312.320
	PSO-8	207.899	19.236	161.560	197.132	208.949	220.740	248.269
	PSO-8-ES	253.922	48.575	169.960	215.347	245.288	279.040	424.875
	PSO-16	206.638	17.691	161.160	197.390	208.380	218.925	248.240
	PSO-16-ES	233.710	32.217	162.880	211.089	232.083	253.307	304.458
	FA-8	234.113	32.577	166.480	209.314	233.150	253.531	308.417
	FA-8-ES	252.813	45.404	167.680	216.413	246.766	292.806	346.074
	FA-16	223.060	25.691	161.520	204.575	225.017	240.929	292.480
	FA-16-ES	236.695	37.064	166.600	212.294	228.557	263.476	326.615
	HS-8	217.204	22.838	163.560	202.906	214.410	231.967	272.042
	HS-8-ES	242.512	36.405	170.200	213.909	244.273	266.536	332.520
	HS-16	212.660	20.859	162.360	201.028	214.716	227.232	258.808
Case Study I (11 NM)	HS-16-ES	233.372	36.421	165.800	208.656	225.667	253.302	340.042
	PSO-8	208.955	21.228	170.294	193.597	205.533	220.794	268.538
	PSO-8-ES	267.800	50.333	182.824	227.025	258.607	291.674	422.500
	PSO-16	206.321	18.148	173.647	194.501	204.067	217.060	260.179
	PSO-16-ES	247.560	42.718	186.774	218.225	238.750	268.126	438.694
	FA-8	247.793	37.667	182.676	221.576	238.196	272.757	368.778
	FA-8-ES	267.948	51.479	188.774	230.593	251.444	302.809	446.028
	FA-16	233.035	39.652	179.613	208.665	221.819	251.461	411.028
	FA-16-ES	250.189	47.124	182.206	216.311	241.419	279.213	450.972
	HS-8	227.100	30.244	169.588	205.153	219.958	249.166	303.744
	HS-8-ES	261.710	55.953	177.529	220.588	251.315	286.418	438.611
	HS-16	217.890	26.732	175.029	201.219	214.455	232.215	321.111
Case Study II (10 NM)	HS-16-ES	245.215	48.538	190.000	216.043	227.750	269.021	450.278
	PSO-8	207.738	16.804	160.433	196.481	209.420	217.678	245.050
	PSO-8-ES	267.733	63.024	183.100	227.284	257.133	293.767	541.306
	PSO-16	206.821	17.169	160.267	194.687	208.530	217.497	247.378
	PSO-16-ES	247.745	51.906	164.967	215.089	244.638	270.550	514.222
	FA-8	242.691	43.156	166.400	211.894	242.791	261.152	403.129
	FA-8-ES	258.524	43.704	177.548	226.834	261.126	276.350	414.595
	FA-16	232.471	37.984	167.133	210.810	229.923	242.751	407.784
	FA-16-ES	249.640	53.523	165.600	212.063	246.689	270.312	460.378
	HS-8	225.893	37.590	169.333	205.881	224.835	238.316	447.839

Table 2 continued

	Metaheuristic	mean	std	min	25%	50%	75%	max
	HS-8-ES	259.910	60.507	168.933	232.749	250.151	277.698	509.677
	HS-16	218.716	33.499	160.967	201.174	218.555	229.639	418.000
Case Study II (11 NM)	HS-16-ES	242.410	48.861	171.667	215.232	237.891	259.128	466.417

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Declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

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