METAHEURISTIC TECHNIQUES FOR AIR TRAFFIC

FLOW MANAGEMENT IN URBAN SPACE

by

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CSE4197 Engineering Project 1

Project Specification Document

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Contents

1 Problem Statement

This project primarily addresses the issue of air traffic flow management in urban space that is likely to arise with the increased use of unmanned aerial vehicles (UAVs) in recent years. In response to this problem, we propose a comprehensive framework to develop route networks of the urban space and to schedule flight demands in an efficient way. The algorithms and metrics we aim to develop are designed to ensure safe and efficient UAV navigation by minimizing travel time and fuel consumption, where our framework ultimately targets to improve the quality of life in urban environments.

2 Problem Description and Motivation

In recent years, there has been a growing interest in integrating UAV flights into urban environments to reduce road traffic in cities. Conventional ground-based transportation methods have a struggle to meet the growing demand for mobility, emphasizing the need for innovative aerial solutions. Companies like Amazon, Alphabet, and Walmart are conducting research to enable delivery of small packages by drones [1], where Urban Air Mobility (UAM) is dedicated to offering reliable and efficient transportation solutions to this problem. Although the number of drone delivery operations is currently not very large, the global market for drone and electric air vehicle operations is expected to reach tens of billions of USD by the early 2030s, according to McKinsey, and approximately 1 trillion USD by 2040, according to Morgan Stanley [2]. This requires advanced steering capabilities that can respond to the dynamic nature of urban environments. Establishing efficient and safe routes to avoid potential collisions and to minimize cost due to the path lengths are vital, especially considering the challenges of adhering to no-fly zones and maintaining safe distance between air vehicles.

Our proposed framework is designed to enhance UAM by developing a well-designed urban air traffic flow management (UATFM) system for the complexities of urban air navigation. Our UATFM system will be based on metaheuristic techniques by considering the flow structure of urban airspace, congestion, and operational efficiency. By presenting alternative algorithms for route network design and air traffic assignments, our framework will offers comprehensive and effective solutions for UAM. This will provide air vehicles to travel more safely, thereby enhancing urban air safety.

In an area poised for significant future growth, the lack of a comprehensive UATFM framework that includes a set of alternative strategies and targets various metrics underscores the importance of this project. We will evaluate and validate our framework with an empirical study by comparing the similar approaches from the literature. In our framework, We aim to solve the challenges caused by the increasing demand for air transition in the safest and most efficient manner possible in urban air space.

3 Main Goal and Objectives

The primary goal of this project is to develop an efficient framework for Urban Air Traffic Flow Management (UATFM) for generating route networks and scheduling flights in urban space. The objectives of our framework are presented below.

Objective 1: For each origin destination (OD) pair of demands, our framework will generate a set of diverse feasible paths in addition to the shortest path that minimizes the route cost.

Objective 2: It is essential to focus on minimizing the distance traveled for each flight while taking into account the overall behavior of the entire system. The framework aims to improve operational performance by the determination of the shortest possible routes for ODs that are satisfied.

Objective 3: The framework is specifically designed to handle and accommodate all take-off requests received by the system at any given time. The objective is to ensure that as many flight demands as possible are successfully satisfied.

Objective 4: Each origin destination pair (OD), preferred takeoff time and maximum endurable delay is provided as part of the flight demand. It is the limit to how long a flight can be delayed. The goal of our scheduling framework is to minimize the total delay for all scheduled flights.

Objective 5: Calculating frequently used links/nodes in the route network is essential to identify potential hot-spots. This approach allows aerial vehicles to be redirected to alternative routes in order to reduce hot-spots.

Objective 6: After a set of OD pairs of flight demands are received and the corresponding flights are scheduled, a new urgent flight demand may be received. It should be scheduled with only rerouting or delaying as few as possible flights.

4 Related Work

In this section, we divided related work into 2 subsections which are UAM and its route network design, UAM Traffic Flow Management.

4.1 Route Network Design

In a related study by Wang et al., they investigated the concept of UAM [3]. In the paper, they proposed UAM route networks in low-altitude airspace in which the goal is to maximize efficiency and safety while minimizing the noise impact. Using the open-source ALOS data of Singapore, they created a grid-based multi-layer route network along with two-way traffic. They defined some areas that are not allowed for aircraft. The network consisted of vertiports, delivery sites. They tried to find feasible origin and destination pairs by solving the k-Shortest Path with Diversity (KSPD) that will be in favor of efficiency, safety, and noise considerations for link cost. Along with some constraints and cost calculations, a similarity metric is introduced to solve the problem.

In another study [2], a route network planning method was developed to design routes in a complex urban environment following a tube-based Concept of Operations (ConOps). In this method, the problem was divided into a single-path planning problem with added prioritization for four urgency-based drone groups. The method was structured into four main modules: Environment Discretization, Individual Route Planning, Route Prioritization, and Network Planning. The purpose of the Environment Discretization module is to generate a grid graph for network planning. In the second module, for each origin-destination (OD) pair, the goal is to determine a collision-free path that minimizes drone energy consumption, ground-level potential risk, and airspace occupancy. Finally, in the route prioritization and network planning stages, prioritization was applied based on urgency, transforming the network planning problem into a sequential planning problem.

Huiping Liu and Bin Yang address the problem of finding the top-k shortest paths with limited similarity, i.e., diverse paths [4]. Their solution is designed to be independent of a specific similarity metric, allowing it to work with different similarity measures, and it accelerates the process by estimating lower bounds for partially explored paths. In the proposed framework, all paths are stored in a priority queue, sorted in ascending order by their lower bounds. They used a best-first search strategy to select a path from the queue. If this path does not reach the destination, it is extended through its neighbors to generate new paths, which are then reinserted into the queue. If the path reaches the destination, its diversity is checked, and if it meets the criteria, it is added to the result set.

4.2 Traffic Flow Management

In the study by Niki Patrinopoulou and colleagues, several traffic capacity balancing methods developed for a UTM system designed for use in highly dense, very low-level urban airspaces were compared [1]. In their proposed system, as UAVs do not have access to future flights or the routes of other UAVs. In the initial stage, the routes for all vehicles are determined. During flight, UAV position data is collected at regular intervals, and traffic density information is updated and shared with other UAVs, allowing them to adjust their routes based on incoming density information. Finally, the main focus of the study examines how restricted urban airspace should be divided into flow control sectors or flow clusters to facilitate dynamic capacity balancing, concluding that small cluster sectors are the optimal choice.

In a study published by Delahaye and colleagues, an air traffic assignment framework for 3D air transport networks in urban airspace is proposed to enable future UAM operations at projected demand levels [5]. Firstly, UAM operations are modeled as flows within a three-dimensional, bidirectional air transport network. For the NP-hard traffic assignment problem, a two-stage optimization approach is presented, utilizing Simulated Annealing (SA) and Dafermos' Algorithm (DA). Experimental results indicate that the optimal combination for this optimization is to apply SA first, followed by DA.

The study conducted by Wang et al. brings in a new approach which is a Quasi-dynamic Air Traffic Assignment model to overcome high-density UAM traffic [6]. The model is formulated as quasi-dynamic optimization problem. They used a macroscopic approach while defining the variables, such that they will not analyze one by one, but they will analyze the flow to determine the optimality. The research included a linear dynamical system to calculate the air traffic complexity. On top of that, they implemented a Simulated Annealing algorithm with a parallelization that made the whole process even more efficient.

In summary, previous research investigated the UAM and its abilities to find feasible paths along with a traffic flow management considered. In today's research domains, there is a need to contribute on UATFM in which we can use genetic algorithms and apply constraints incrementally.

5 Scope

The project we will be working on is essentially a continuation and integration of two projects conducted last year in the Computer Engineering Department at Marmara University. We will refine the project led by Murathan Akman, Ahmet Onat Özalan, and Burak Aslan, enhancing it with a more effective algorithm.

In the Urban Air Mobility field, our project will leverage the UAM route network design developed last year, implementing an algorithm based on this design to identify safe, optimal, and diverse routes between each origin-destination pair. Subsequently, by utilizing genetic algorithms, we aim to ensure that the maximum number of UAVs reach their destinations with minimal fuel consumption, flight time, and conflict. Additionally, by assessing air density during route planning, we aim to optimize routes to avoid high-traffic areas. The general constraints of our project are listed below:

- We will assume that the UAVs may have different speeds from one another; however, each UAV's speed will remain constant during its flight.
- As mentioned in Section 6.3.1, we will perform grid-based discretization. Here, if we denote the discretization grid size as d_g, any pair of potential waypoints should have a distance no greater than $\sqrt{2}\,d_g$. This implies that aerial vehicles cannot move diagonally upward across the grid [3].

6 Methodology and Technical Approach

In this section we first summarize terminology, which is followed by the details of our framework.

6.1 Terminology

Urban Air Mobility (UAM): With the increasing use of aerial vehicles, undesirable issues such as complex traffic situations and delays are expected to arise. Consequently, innovative mobility solutions are required to ensure safe and efficient urban transportation. Urban air mobility (UAM) is an air transportation concept that supports passenger or cargo-carrying air transportation services in and around urban environments [3]. In particular, Unmanned Aerial Vehicles (UAVs) play an important role in UAM operations within low-altitude urban airspace such as passenger transportation, parcel delivery, and traffic monitoring.

Airspace Structure: Along with other route network assumptions, we need an urban airspace structure for our framework. In literature, there are two compilation articles for urban airspace structures. Jang et al. defined that there are three types of airspace designs which are sky-lanes, sky-tubes, and sky-corridors [7]. Ui-Jeong Lee et al. stated some designs which are similar to the first one, as named Air-Matrix, Air-Network, and Air-Tubes [8]. We found that sky-lanes will be the most suitable option for our framework. Sky-lanes use a lane-based design which provides us an organized multiple layers to minimize conflicts. Using layering in lanes at different altitudes, they maximize the efficient use of urban air space while handling high traffic volumes. However, they need to be monitored in intersections, and high-traffic points. Along with that, in rush hours there may be congestion in intersections.

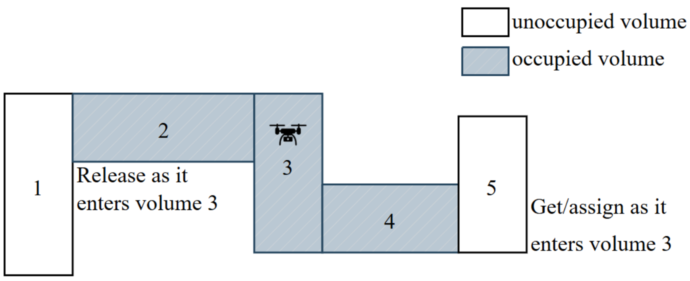

Figure 1: The Airspace Structure and Allocation of Our Project[8]

In sky-lanes, they introduced priority-based rules to determine the UAV which has the right at intersections. They overcome the problem by assigning priorities based on mission types. Also scheduled time slots allocated for entering an intersection are defined. Adjusting speed and maintaining safe zones also avoids risks. There can be virtual traffic lights and holding patterns as well. Along with these, changing lanes or altitude in merge points will prevent collisions. Lastly, conflict resolutions happen by rerouting alternative paths. Our sky-lane design will consist of a temporal allocation of airspace. As can be in the Figure 1, we will occupy the lane or volume and release and assign accordingly.

Geofences: Unlike the high-altitude controlled airspace with few obstacles, the low-altitude airspace needs to consider the geospatial complexity derived from geometric variability of existing static obstacles. In this matter, Geofence is a widely used concept to ensure safe separation of UAVs. Geofence is categorized into two types based on its purpose, keep-out and keep-in [9]. A keep-out geofence defines and creates a buffer space of fixed magnitude around ground structures. In our project, it is 30m away from the existing obstacles. On the other hand, A keep-in geofence is defined as a spherical ball to contain a vehicle. In our study, this is not be taken into account.

Layering: The layering concept focuses on dividing airspace into distinct layers to ensure safe and efficient air traffic management for UAVs .There are mainly three key types of layers: cruise layer, turning layer, and buffer layer[10]. The cruise layer facilitates organized horizontal flight paths, while the turning layer is specifically designed for vertical maneuvers. The buffer layer provide separation between active layers, minimizing the risk of intrusion of UAVs that operating in adjacent layers. Our study will delve deeper into the layering concept during the second stage of the project (see Section 6.5).

6.2 Our Framework for Urban Air Mobility

Our framework, as shown in Figure 2, consists of three main stages: UAM Route Network, OD Paths Generation, and UATFM (Urban Air Mobility Flow Management). The red-shaded sections in Figure 2 indicate the components that were completed and provided from last year's CSE4197-98 project.

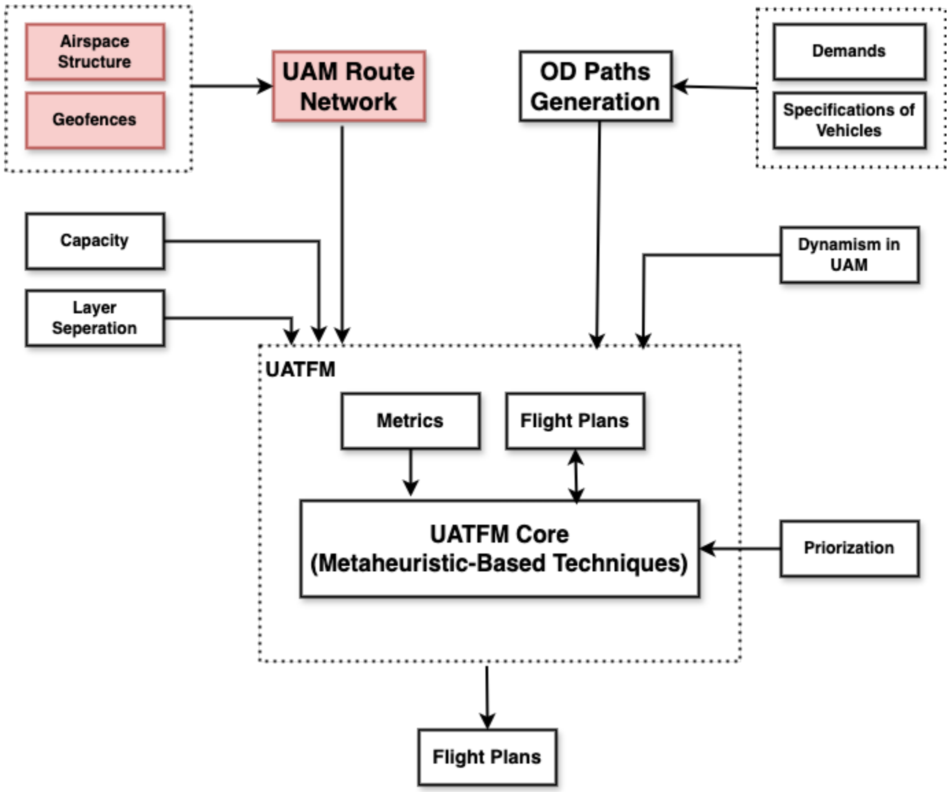

Figure 2: The General Scheme of Our Framework

Our first motivation (as presented at Section 6.3.2) is to extend and improve the OD Path Generation stage with additional algorithms (A* [2] or D* Lite [1]) and similarity metrics. The performance evaluation of algorithms with various similarity metrics will be provided as part of this study.

The primary focus of our project will be the core part of the UATFM. Based on the metrics provided, we will design and implement to develop flight plans to minimize UAV delays in air traffic. In the event of congestion, prioritization will enable high-priority aircraft to reach their destinations more quickly. Additionally, we aim to make our project dynamic, allowing us to accommodate new flight requests with optimal routes even after the initial route planning is completed.

6.3 Route Network Design in Our Framework

To represent our route network of urban airspace, we directly used calculations of a case study focused on the urban airspace in Singapore [3]. In the study, the researchers utilized Singapore's airspace classification information. To streamline the search space and reduce the costs associated with network construction, the Axisaligned Minimum-Area Bounding Box (AMABB) encompassing the vertiports and delivery sites was calculated. This provided a minimum spatial area for designing the route networks. The goal was to identify candidate paths that would maximize flight safety and efficiency, minimize noise impact on nearby populations, and adhere to operational constraints. The method known as k-Shortest Paths with Diversity (KSPD) was employed. The resulting multi-layer route network is illustrated in Figure 3, where the vertiports, delivery sites, and waypoints are marked. Links at five different altitude layers are distinguished by different colors.

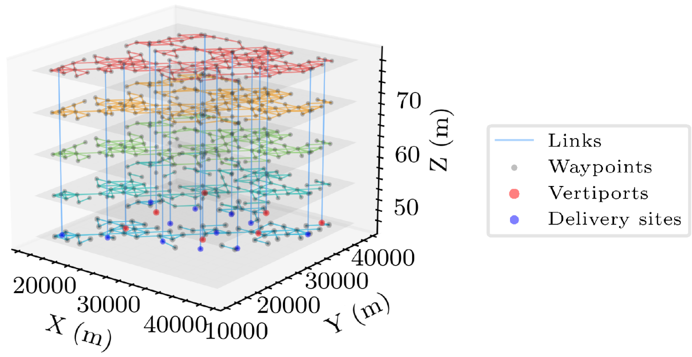

Figure 3: Route Network of Singapore [3]

6.3.1 Problem Formulation

In this section, we present the formal definition of the problem with a set of equations. First, the length of the path that the UAV will travel, denoted as d_p, should not exceed the maximum range of the UAV, denoted as R_{max}[3]:

$$d_p < R_{\text{max}}, \quad p \in P \tag{1}$$

Also, the flight time should be limited to the endurance of the UAV[3]:

$$\sum_{e \in p} \frac{X_{de}}{s_e} < T_{\text{max}}, \quad p \in P \tag{2}$$

where s_e is the average speed of UAM traffic flow on link e.

The cost of flight efficiency is calculated based on link length d_e and the type of link[3]:

$$C_{f,e} = (\phi_h \delta_{e,h} + \phi_u \delta_{e,u} + \phi_d \delta_{e,d}) d_e \tag{3}$$

Each variable in the formula is defined as follows: $\delta_{e,h}$ is an indicator that equals 1 if link e is horizontal, otherwise it is 0; $\delta_{e,u}$ is an indicator that equals 1 if link e is upward, otherwise it is 0; $\delta_{e,d}$ is an indicator that equals 1 if link e is downward, otherwise it is 0; ϕ_h, ϕ_u, and ϕ_d are the efficiency coefficients for horizontal, upward, and downward links, respectively.

6.3.2 New Extensions for OD Path Generations

There is a need to improve the solutions from the UAM route network (developed from the previous work), so we will utilize some path planning algorithms for this stage.
KSPD Similarity Rate Changing: Based on a similar work in the literature [3], we will rework on a K-Shortest Paths with Diversity algorithm where we utilize two similarity rates in equations (4) and (5) in our algorithms [4]. Along with the rate changes, we will apply A*, θ* or D* Lite instead of the Dijkstra that was used in the related work. We will design a set of experiments with these extensions and validate our extensions to improve the OD pairs generated.

$$Sim_1(P_i, P_j) = \frac{L(S_{P_i} \cap S_{P_j})}{L(S_{P_i} \cup S_{P_j})} \tag{4}$$

$$Sim_2(P_i, P_j) = \frac{L(S_{P_i} \cap S_{P_j})}{2L(P_i)} + \frac{L(S_{P_i} \cap S_{P_j})}{2L(P_j)} \tag{5}$$

A*: A* path planning algorithm was developed to find minimum cost path by using heuristic information to make nodes expanded selectively and it reduces the computation complexity [11]. By identifying the least cost route in the graph, it calculates each node's cost which is f(n) by adding a path cost from the start to the node which is g(n) to the h(n) which is an estimation of the cost to the goal. It expands the nodes with lowest f(n) values, A* is said to be optimal if the heuristic defined is admissible and consistent. So, A* can be used to various constraints easily in path finding. Its performance depends on how well defined the heuristics. However, it can cause high space complexity, especially in large or complex graphs.

$$f(n) = g(n) + h(n) \tag{6}$$

θ*: The θ* path planning algorithm was developed to optimize paths on grid-based terrains by enabling paths to cross grid cells freely [12]. This will also approximate a true shortest path in the continuous state. First, it starts with a start node with zero path cost, while all others have infinite costs since they are not explored yet. By expanding nodes from an open list, θ* evaluates paths to visible nodes through line-of-sight checks which allows them to bypass unnecessary nodes therefore reducing the path length and complexity. Paths dynamically updated for parent nodes and path costs, which refines the route iteratively. Backtracking was done to reconstruct the path after the destination is reached. While generating nearly optimal paths, the frequent line-of-sight checks increase computation in complex environments.

D* Lite: D* Lite is introduced as an incremental path finding algorithms in dynamic environments by using previous computations rather than calculating from scratch again [13]. Derived from the lifelong planning A* framework, D* Lite combines heuristic with incremental search which updates only for nodes affected by changes in costs. At first, D* Lite starts with assigning node costs and managing nodes in a priority queue based on the key values which include the path and the heuristic costs. If a change occurs, only affected path segments were recalculated by the algorithm. By using localized lazy updates and a key-offset technique for minimal queue adjustments, efficiency was guaranteed. Although being efficient in dynamic environments, if a large change occurs the performance may be low.

6.4 Hybrid Evolutionary Algorithms for UATFM Framework

In this section, we will discuss the evolutionary algorithms that will be used in the core part of our project, specifically in the UATFM module shown in Figure 2.

Evolutionary algorithms are based on the principle of natural selection, where the fittest individuals in a population survive. The primary goal is to maximize (or minimize) a defined quality function. Based on the quality function, those with the highest values are selected, and offspring (new candidates) are generated through recombination and mutation operators. The fitness of these new candidates is then evaluated and compared with that of the previous generation to determine which individuals will move on to the next generation. This process continues until a high-quality individual or a specified computational limit is reached [14].

While simple EAs can be readily developed for many optimization challenges, their efficiency tends to be limited, especially for handling complex combinatorial problems [14]. To enhance the performance of EAs, integration with problem-specific knowledge becomes a common strategy, which can be in the form of combining specialized operators or algorithms with EAs to create sophisticated hybrid systems (called Hybrid Evolutionary Algorithms). We will design hybrid evolutionary algorithms for the urban air traffic flow management problem to generate congestion-free trajectories by considering demand and capacity balancing.

6.5 Milestones of our for UATFM Framework

We plan to develop our UATFM Framework in three consecutive stages, where an empirical study will be performed to validate each stage.

Stage 1: In the initial stage of our project, we will first establish our framework with its core requirements. At this stage, the structure we build will be static. This means that all flight demands will be assumed to be known prior to planning, and no additional demands will be introduced after the flights have been scheduled. Additionally, we will prioritize UAVs based on their different characteristics, allowing higher-priority vehicles to reach their destinations more quickly than others. Also, we will assume that the speed of the vehicles will remain constant or be zero during flight. To optimize the routes, we will utilize the algorithms discussed in Section 6.4.1.

Stage 2: The second stage of the project focuses on UAV safe separation through airspace layering and interaction rules. In this approach, airspace is divided into layers—cruise, turn, and buffer—each designated a specific range of headings to reduce collision risks. UAVs primarily operate in cruise layers, and our study emphasizes the Baseline Air Structure over the 1-1 Air Structure [10].

Airspace allocation rules include Baseline, Density, Random, and Flight Distance methods [10]. The Baseline rule maintains vertical separation, allowing faster UAVs to ascend for overtaking. The Density method assigns UAVs to the least crowded layer, prioritizing lower layers when options are equal. Random allocation promotes uniform distribution without considering layer occupancy, while the Flight Distance method assigns lower layers to shorter flights and higher layers to longer ones. Our study will analyze these methods and their trade-offs to identify the most effective approach for the framework.

Stage 3: In this stage, we aim to add quasi-dynamic and Machine Learning based estimations. By quasi-dynamic, not fully dynamic but close to being dynamic is meant [6]. In our case, we will implement time frames to our framework which will be based on a rolling horizon approach that is decisions made at a interval and updating progressively. Also, we will be implementing a ML Algorithm (the LSTM) for demand forecasting. LSTM models succeeded at demand forecasting tasks by effectively handling time series data with complex patterns and dependencies while enabling accurate predictions even in dynamic cases [15]. This will help with identifying patterns and preplanning.

6.6 Differences Between Previous Year's CSE4197-98 Projects

Our project relies on long-term research done by last year's graduate students. To give precise separation, there were two projects done previously and below statements are our differences from their projects.

Project on UAM Route Network: One of the last year's CSE4197-98 projects was on UAM route network where they generated UAM Route Network in Singapore's airspace. They implemented a KSPD algorithm to find the origin-destination pairs with an extension of Yen's Algorithm. By using their implementations on geofences and system model, we will study improvements on generating more efficient OD pairs. We will implement new set of algorithms (A*, D* Lite and θ*), along with the different similarity equations on the algorithm that they had implemented.

UAM Traffic Flow Management: One of the last year's project was on UAM traffic flow management. They designed a GA-based implementation which was partially mapped only the first stage of this project (See 6.5). Their design does not input UAM route network presented in this report and they do not consider variable velocities and different delay requirements. Since all stages of this project are different and their assumptions do not match, we will not utilize their output in our framework.

7 Professional Considerations

In this section, we point out the methodological considerations, realistic constraints, and legal dimensions related to the project's development and deployment.

7.1 Methodological Considerations/Engineering Standards

Algorithm Implementation: We chose to implement our algorithms using the Python programming language since it offers a wide range of libraries and built-in functions specifically for Genetic Algorithms. Additionally, we decided to use the C programming language to design our data structures, as C provides significant flexibility in building these structures.

Version Control: We will manage our source code using the Git version control system, hosted on platforms like GitHub. This approach will enhance collaboration, code versioning, and revision tracking among team members.

Project Management: We will primarily use Dropbox, a file hosting service and sharing platform. We utilize this platform for reading articles, sharing example source codes, and documenting our weekly meeting minutes.

Design Documentation: We will use diagrams to clearly illustrate the system architecture, data structures, and algorithmic workflows by using Miro. To visualizing data, we will use Microsoft Excel and QGIS.

7.2 Realistic Constraints

The design of the project will carefully take into account a variety of realistic constraints, including economic, environmental, ethical, health and safety, sustainability and social considerations.

Economic: We aim to reduce costs for software development and testing in our project by using open source and student-friendly support platforms whenever possible.

Environmental: We think that the simulations we will use, especially during the testing phase, will create some environmental restrictions, as our computers' power and long-term working capacity are limited.

Ethical: Our project does not present any ethical issues since the sources we use are reliable and accurate, with each one cited in the reference section.

Health and Safety: Our project operates autonomously, ensuring a safe environment free from health and safety concerns. It functions independently, without any external influences or factors that could introduce potential risks.

Sustainability: The project focuses on developing sustainable optimization methodologies for Urban Air Mobility (UAM) through the application of evolutionary algorithms.

Social: There are no social constraints since the framework is still in the development phase and there has been no interaction with end users. However in the future, the project will effect human life and change our traditions by increasing the use of UAVs.

Legal Constraints: There are no legal concerns associated with this study since our study uses open-source platforms. A comprehensive list of the sources referenced will be provided in the reference section, ensuring transparency, and allowing readers to explore the materials in detail.

8 Management Plan

8.1 Description of Task Phases

Phase 1: Literature survey on UATFM and applications on metaheuristics.

Phase 2: Implementation of path finding algorithms to improve KSPD with testing.

Phase 3: Implementation of hybrid genetic algorithms to control the traffic flow with testing.

Phase 4: Adding a separation layer to the basic UATFM model with testing.

Phase 5: Making our model applicable to dynamic environments with testing.

Phase 6: Applying machine learning to estimate similar flight demands beforehand with testing.

Phase 7: General testing of whole model including stress tests.

8.2 Division of Responsibilities and Duties among Team Members

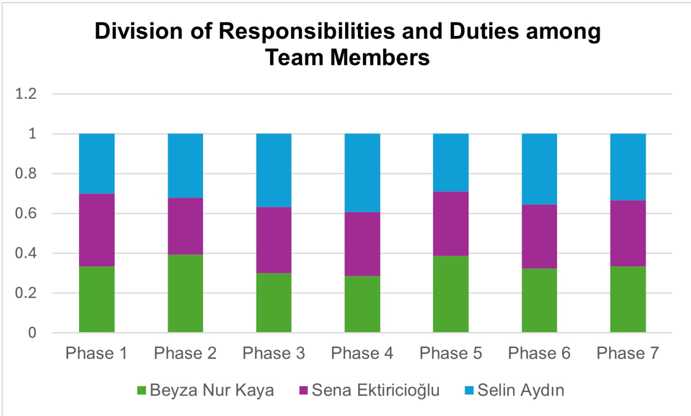

Figure 4: Division of Responsibilities and Duties

8.3 Timeline

Objectives	Sept. 2024	Oct. 2024	Nov. 2024	Dec. 2024	Jan. 2025	Feb. 2025	Mar. 2025	Apr. 2025	May. 2025	Jun. 2025
Phase 1										
Phase 2										
Phase 3										
Phase 4										
Phase 5										
Phase 6										
Phase 7										

Figure 5: Timeline

9 Success Factors and Risk Management

9.1 Measurability/Measuring Success

- **Objective 1:** For each origin destination (OD) pair of demands, our framework will generate a set of diverse feasible paths in addition to the shortest path that minimizes the route cost.

  Success Factor 1: Based on the alternative algorithms presented as part of the framework, the frameprk will provide *7* different shortest paths with some level of diversity among them by utilizing *2* different similarity metrics presented in the framework.

- **Objective 2:** It is essential to focus on minimizing the distance traveled for each flight while taking into account the overall behavior of the entire system. The framework aims to improve operational performance by the determination of the shortest possible routes for ODs that are satisfied.

  Success Factor 2: The length of the shortest path for each individual flight and the length of the possible shortest path within the network while thinking the entire system are two main dependent variables for the success rate of the given objective [1]. The ratio of the total length of shortest paths over the total length of the possible shortest paths should be less than 70%.

- **Objective 3:**The framework is specifically designed to handle and accommodate all take-off requests received by the system at any given time. The objective is to ensure that as many flight demands as possible are successfully satisfied.

  Success Factor 3: It is crucial to schedule flight requests within our framework as much as possible, aiming to schedule with a satisfy rate of 80%.

- **Objective 4:** Each origin destination pair (OD), preferred takeoff time and maximum endurable delay is provided as part of the flight demand. It is the limit to how long a flight can be delayed. The goal of our scheduling framework is to minimize the total delay for all scheduled flights.

  Success Factor 4: Our goal is to schedule flight requests without exceeding the maximum delay capacity for each flight. To achieve that, we will aim to reduce the delay, without considering routing, by 20%.

- **Objective 5:** Calculating frequently used links/nodes in the route network is essential to identify potential hot-spots. This approach allows aerial vehicles to be redirected to alternative routes in order to reduce hot-spots.

  Success Factor 5: Frequent use of certain nodes can create hot-spots, which in turn increases the delays for flights. We expect to see a remarkable difference in flight delay times once we integrate this hot-spot prediction subsystem into our framework. This extension will result in a 10% improvement in the objective function.

- **Objective 6:** After a set of OD pairs of flight demands are received and the corresponding flights are scheduled, a new urgent flight demand may be received. It should be scheduled with only rerouting or delaying as few as possible flights.

  Success Factor 6: For this type of quasi-dynamic cases, the framework targets to either cancel a single flight or delays up to 3 flights.

9.2 Risk Management

During the development process, several risks may affect the project, each with a corresponding resolution strategy. If access to the requested dataset from BlueSky fails, we will generate synthetic simulation data to create the required dataset. In the event of challenges in implementing our simulation and testing mechanisms, BlueSky's simulation tools will be utilized as an alternative. To address potential failures in converging to suboptimal solutions, advanced mutation, and crossover strategies, along with other optimization techniques, will be employed. Lastly, to manage high computational complexity, parallelization will be used to reduce problem-solving time effectively.

10 Benefits and Impact of the Project

In recent years, there has been increasing interest in integrating UAV flights into urban environments, and this interest is expected to grow in the future. For instance, in a metropolis like Paris, demand for Urban Air Mobility vehicles for deliveries is projected to reach up to 8,333 per hour by 2035 [6]. Unfortunately, this expansion brings challenges, including increased low-altitude air traffic density, safety concerns, noise pollution, and energy consumption. Through the algorithms we will develop, UAVs will achieve safe and efficient travel, reducing travel time and fuel consumption, thereby contributing to an improved quality of life in cities.

(i) **Scientific Impact:** Our proposed project, which will be developed in the emerging field of UAM, aims to address the challenges in this area. As we discussed in Section 4, there are indeed high-quality studies in the literature; however, the problem has yet to be definitively solved. The methodologies and algorithms we develop have the potential to enrich the body of knowledge by being published in scientific journals.

(ii) **Economic/Commercial/Social Impact:** Our project aims to provide low-cost, safe UAV transportation and related services by delivering an optimization system for UAM service providers. By optimizing routes and air traffic, it reduces UAV traffic congestion, flight durations, and fuel consumption, minimizing waste. Socially, it enhances quality of life with fast, safe, cost-effective, and eco-friendly air transportation solutions.

(iii) **Potential Impact on New Projects:** For this relatively new field, there are valuable studies in the literature; however, their number is still limited. Therefore, we believe that our work will make a significant academic contribution in this area.

(iv) **Impact on National Security:** Our project did not affect national security.

References

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