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Simulation-Based Unmanned Aerial Vehicle Fleet Management and Control System for Urban U-Space

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ABSTRACT

The Simulation-Based Unmanned Aerial Vehicle Fleet Management and Control System for Urban U-Space (S-UFMC) is an advanced framework designed to manage high-density UAV traffic within complex urban environments. To ensure safe, efficient and scalable operations, the system employs a grid-based airspace model that segments the urban environment into manageable 3D corridors. This structure is governed by a synthesis of artificial intelligence (AI), A (A-STAR) pathfinding algorithms and a suite of simulated sensors. Performance monitoring relies on simulated IoT sensors, which operate using data models derived from extensive research and testing. These simulations track key metrics such as speed, total path length and average velocity to guide operational decisions. Safety is paramount, enforced by an anti-collision system that uses simulated LiDAR and proximity sensors to predict and resolve potential conflicts in real time. The system's AI core, enhanced by reinforcement learning, facilitates intelligent decision-making. This allows for real-time trajectory adjustments and dynamic rerouting to navigate obstacles, fluctuating traffic density and other environmental changes. A robust simulation platform validates the entire system, allowing for comprehensive testing of algorithms and behaviours across diverse operational scenarios to ensure real-world reliability which sets a new standard for urban air traffic, enabling safe drone applications in smart cities.*

Keywords: UAV, Urban Air Traffic Management System, A* Algorithm, Reinforcement Learning, Grid-based Airspace

1. INTRODUCTION

The rapid advancement of Unmanned Aerial Vehicles (UAVs) has revolutionized sectors such as logistics and agriculture, yet their integration into dense urban environments remains challenging due to physical obstacles and unpredictable traffic patterns [1][2][3]. Existing air traffic control systems are ill-equipped to handle these unique low-altitude operations, necessitating specialized management structures for collision avoidance and real-time adaptation to environmental hazards. To address the issue, this research proposes a Simulation-Based Unmanned Aerial Vehicle Fleet Management and Control System for Urban U-Space (S-UFMC) that utilizes IoT technologies and advanced algorithms to facilitate dynamic communication [4]. Furthermore, the system implements a grid-based airspace model to divide complex urban environments into manageable zones, thereby enhancing monitoring precision

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and control. This project focuses on developing a scalable, simulation-based proof of concept to ensure the safe and efficient coordination of future urban drone traffic [5].

This research aims to bridge the gap between theoretical UAV traffic management and practical urban application. The main contributions of this work are:

- Design of a 3D Grid-Based Architecture: We designed a UFMC architecture that uses a grid-based model to manage complex urban U-Space.
- Integration of Pathfinding Algorithms: We integrated A* and 3D Q-learning algorithms to ensure safe path planning and trajectory optimization.
- Multi-UAV Simulation with Dynamic Hazards: We implemented a simulation for up to three UAVs that adapts to dynamic weather zones and static obstacles.
- Cloud-Based IoT Dashboard: We developed a real-time monitoring dashboard using Firebase and React to visualize critical telemetry data.

1.1 Overview of UAV and Urban Airspace Management

UAVs are revolutionizing industries in logistics and surveillance through advancements in AI and IoT, necessitating specialized UAV Traffic Management Systems (UTM) to ensure safe and efficient operations [6]. These systems rely on essential elements like collision avoidance and dynamic pathfinding using algorithms such as A* and Particle Swarm Optimization [7]. Originally developed for military use, these pilotless aircraft have expanded into civilian sectors like agriculture and infrastructure inspection [8]. As UAVs become central to urban and environmental applications, adherence to low-altitude airspace regulations, such as those overseen by Malaysia's CAAM, is critical for safety [9]. To address these challenges, the S-UFMC integrates Graph Theory and Air Traffic Flow Theories to create structured, manageable environments for operations. By employing grid-based airspace modelling, the system effectively prevents collisions and reduces congestion in urban areas.

1.2 Algorithms and Core Components of S-UFMC

The S-UFMC employs primary algorithms like A* to optimize route planning and handle obstacle avoidance within both static and dynamic environments. This algorithmic approach is supported by Grid-Based Airspace Modelling, which divides urban airspace into manageable sectors for better control. Advanced technologies such as Machine Learning refine pathfinding, while Reinforcement Learning enables UAVs to dynamically adjust to changing conditions based on real-time feedback [10]. For operations involving multiple drones, Swarm Intelligence allows for collaborative navigation, ensuring efficiency in high-density areas [11]. The system's architecture relies on simulated sensors, including LiDAR and GPS, to replicate real-world data for stability and positioning. Crucial to this setup are communication modules supporting Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) links, which ensure low-latency control and prevent mid-air collisions [12]. Globally, while standardized commercial systems are not yet in place, organizations like NASA are leading progress with proposed frameworks for Urban Air Mobility. Simulation platforms such as MATLAB and Gazebo are essential for testing these dynamic pathfinding technologies. Despite existing regulatory challenges, ongoing research points towards a promising future for the large-scale implementation of these systems in urban settings.

The S-UFMC framework addresses critical operational challenges such as loss of communication and unreachable targets through a combination of automated fail-safe protocols and adaptive algorithms. To mitigate the risks associated with communication failure, the system's flight controller module simulates specific fail-safe mechanisms, including an automated return-to-home function that guides the UAV back to a safe location if the connection to the ground control station is severed. This is reinforced by Command-and-Control links designed with redundancy to maintain control even if primary channels fail. In scenarios where targets become unreachable due to environmental hazards, the system employs a strict mission halt protocol. If a UAV's planned path intersects with dynamic threats like bad weather zones or static restrictions like no-fly zones, the system immediately stops the mission to prevent the aircraft from entering dangerous conditions. Furthermore, for targets obstructed by complex obstacles rather than absolute restrictions, the system utilizes Reinforcement Learning; specifically, the UAV employs Q-learning to adapt its trajectory through trial and error, attempting to identify alternative optimal paths that avoid obstacles while minimizing penalties.

1.3 Summary of Previous Works

A review of previous works in UAV fleet management and control reveals significant progress in optimizing urban airspace for drone operations, though challenges remain. Studies like [12] work on the UTM framework for urban environments demonstrated real-world trials with communication technologies like V2V and V2I, achieving high automation in UAV traffic management but missing grid-based airspace modeling and dynamic path planning. In [13], researchers are studying on public air route network planning used Voronoi diagrams and A* algorithm to optimize urban UAV paths, enhancing safety and efficiency by reducing flight times and risk, but lacked IoT integration. Particle Swarm Optimization (PSO) was used for swarm intelligence-based UAV navigation showed improvements in scalability and memory efficiency for multi-agent systems, but didn't incorporate reinforcement learning (RL) or real-time updates [11]. Similarly, smart city integration with GIS-based navigation and automated systems are used in [7] for UAVs provided efficient, conflict-free operations but was limited by its reliance on fixed air routes. Finally, work in [8] integrated UAVs into intelligent transportation systems through data collection and real-time monitoring improved traffic management but lacked specific collision avoidance algorithms. Collectively, while these studies showcase substantial progress, further research is required in areas like dynamic pathfinding, real-time data integration, and scalable systems for effective urban UAV traffic management.

To address these limitations, this research proposes the Simulation-Based Unmanned Aerial Vehicle Fleet Management and Control System for urban U-Space (S-UFMC). Unlike previous frameworks, the S-UFMC integrates grid-based airspace modeling with a robust IoT architecture to enable precise, real-time monitoring of high-density traffic. Furthermore, the system synthesizes the A algorithm* for efficient obstacle avoidance and RL, specifically 3D Q-learning, to allow for autonomous, dynamic pathfinding and trajectory optimization that adapts to environmental changes like weather hazards. By combining these advanced algorithms with cloud-based telemetry visualization, the proposed system offers a scalable, conflict-free solution that overcomes the reliance on fixed routes and static planning seen in earlier studies.

2. MATERIAL AND METHODS

The methodology outlines the development of S-UFMC, designed to manage urban drone traffic through simulation. The system's architecture relies on a grid-based airspace model, integrating IoT, machine learning, and cloud platforms for scalable operations. Key algorithms include A* for collision avoidance and RL for dynamic path optimization, with IoT protocols facilitating real-time communication. The project follows a structured five-phase development process: it begins with System Design to define the architecture, followed by Software Development to implement the A* and RL algorithms and communication protocols like MQTT. Next, Operational Testing uses MATLAB simulations to validate the system in realistic urban scenarios. This is followed by Data Integration, which establishes real-time IoT data transfer to the cloud (like Firebase) for AI-driven analytics. Finally, Interface Development involves creating dashboards and mobile apps for operators to monitor and control the UAV fleet. The project follows a structured five-phase development process, as illustrated in Figure 1.

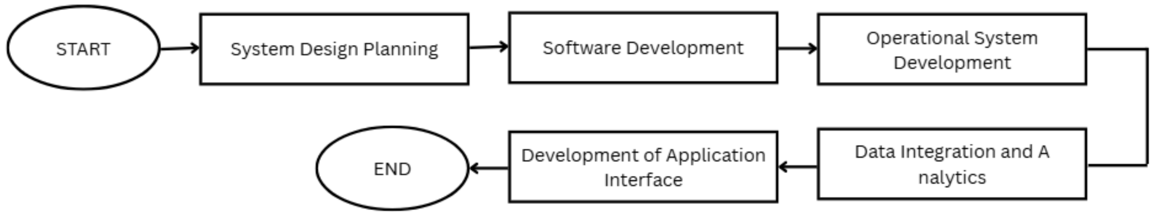

Figure 1. Project development flowchart

2.1 System Design Planning

The system design planning phase establishes the foundational architecture of the S-UFMC, utilizing a grid-based airspace model to divide urban environments into manageable sections for precise control. This phase coordinates core components, such as UAV control systems and communication modules, while defining critical operational parameters like flight paths and real-time data exchange protocols. Additionally, optimization algorithms such as A* and Reinforcement Learning are integrated to ensure safe navigation and effective obstacle avoidance within high-density urban airspaces.

By referring to Figure 2, the No-Fly Zone is a red dome-shaped within the 3D airspace, representing restricted areas like military bases or airports. It is integrated into the occupancy map, preventing the UAV from entering, while the pathfinding algorithms (A* and Reinforcement Learning) ensure the UAV avoids these areas. The zone is visualized with semi-transparency and labelled to emphasize its importance. Meanwhile, the Bad Weather Zone is a blue cylindrical region, simulating dynamic weather conditions such as storms or turbulence. Its position and size are dynamically generated, and the UAV's pathfinding algorithms are forced to adjust to avoid this hazardous area. The zone is integrated into the occupancy map to ensure the UAV navigates around it safely, testing the system's adaptability to changing environmental factors.

The system defines the following start and goal station coordinates for the UAVs:
Start Stations:

- Station 1: [190, 190, 1]
- Station 2: [190, 90, 1]
- Station 3: [190, 10, 1]

Goal Stations:

- Station 1: [10, 190, 1]
- Station 2: [10, 90, 1]
- Station 3: [10, 10, 1]

These coordinates are used to set the starting and destination points for each UAV, which can be customized by the user for different flight scenarios.

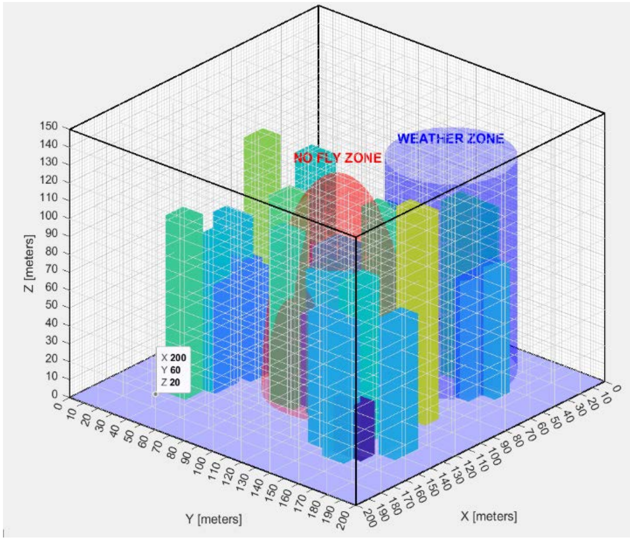

Figure 2. 3D environment with No-Fly Zone and Bad Weather Zone

2.2 Software Development – A* Algorithm

The software development for S-UFMC includes the implementation of pathfinding algorithms like A* for trajectory optimization, which is a crucial component of the system.

2.2.1 2D A Path Planning and Obstacle Avoidance*

In the initial phase, the A* algorithm was implemented in a 2D grid environment, as shown in Figure 3, where each cell represented either free space or an obstacle. The algorithm prioritized paths by calculating the g-cost (actual cost to reach a node), h-cost (heuristic estimate of the cost to the goal), and f-cost (total estimated cost). Testing involved simple and complex scenarios, including paths with obstacles and multiple UAVs, to assess the algorithm's ability to dynamically adjust when obstacles were introduced. The algorithm successfully recalculated optimal paths around obstacles, demonstrating its efficiency in grid-based environments.

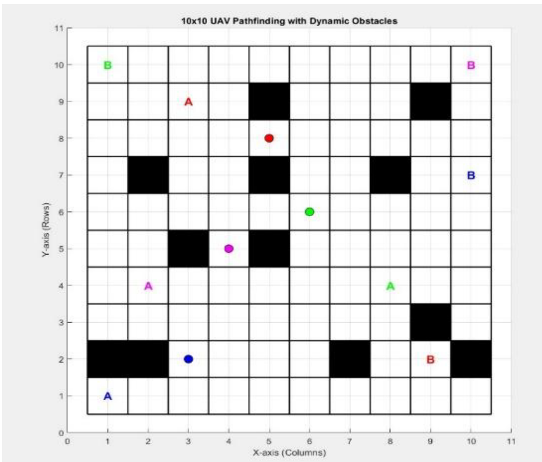

Figure 3. 2D A* path planning with obstacles

2.2.2 3D A Path Planning and Obstacle Avoidance*

Following the success of 2D testing, the A* algorithm was adapted to a 3D environment, as shown in Figure 4. This required incorporating altitude into the grid, adding the complexity of movement across three axes (X, Y, and Z). The transition from 2D to 3D introduced additional challenges, including the need to consider vertical movement and the potential for collisions in the airspace. The UAVs' paths were recalculated dynamically, ensuring safe navigation through both horizontal and vertical spaces, with obstacles effectively avoided in all directions. This adaptation made the system more suitable for real-world urban airspace simulations where UAVs must navigate through complex three-dimensional environments. The A* algorithm, when implemented in both 2D and 3D, successfully ensures efficient and safe navigation by recalculating paths to avoid obstacles and adapt to dynamic changes in the environment.

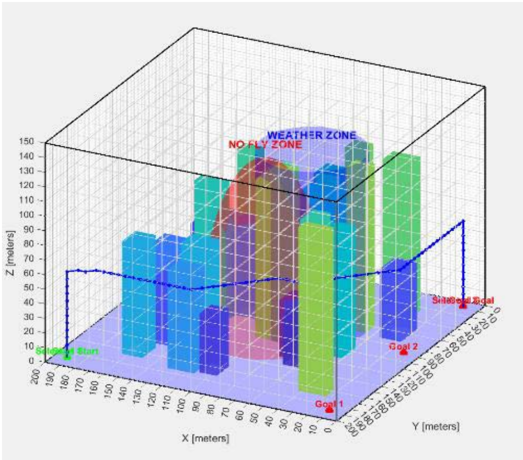

Figure 4. A* path planning in 3D environment

2.3 Software Development – Reinforcement Learning

The S-UFMC applies a 3D Q-learning algorithm to UAV pathfinding, as shown in Figure 5, enabling an agent to navigate from a designated start position to a goal while avoiding randomly placed static obstacles. Through reinforcement learning, the UAV autonomously updates a Q-table via trial and error, optimizing its trajectory to minimize travel distance and ensure safety, which is visualized as a series of connected blue dots. The algorithm is specifically tuned for rapid adaptation and extensive exploration using a high learning rate (alpha = 0.6), for quick strategy updates and a discount factor (gamma = 0.95), to prioritize long-term objectives. Additionally, the exploration rate (epsilon) begins at 0.9 and decays slowly by 0.999 per episode to a floor of 0.05, ensuring the agent thoroughly explores the environment to avoid suboptimal paths before converging on the best route for complex 3D navigation. A reward structure in the Q-learning algorithm is designed to guide the UAV toward optimal navigation behaviours by balancing primary objectives with safety and efficiency constraints. At the core of this structure is a significant positive reward of 500 for successfully reaching the goal coordinates, which serves as the ultimate target for the agent. To ensure safety, the system applies a severe penalty of -200 whenever the UAV collides with an obstacle or attempts to move outside the grid boundaries, effectively teaching the agent to avoid hazardous areas. Operational efficiency is encouraged through a small base step cost of -0.005 for every move taken, which penalizes longer paths and promotes the discovery of the shortest route. Additionally, a dynamic progress reward, weighted at 20, provides immediate feedback by calculating the difference in distance to the goal between the current and previous steps, rewarding movement toward the target and penalizing movement away from it.

Specific flight behaviours are enforced through a set of altitude-based constraints designed to simulate realistic flight patterns. The system encourages the UAV to maintain a specific cruise altitude of 20 meters by applying a penalty factor of 0.5 based on the vertical deviation from this target height. To prioritize safe lift-off, a heavy penalty of -10 is imposed if the UAV is below the cruise altitude and takes an action that does not increase its height. Furthermore, a penalty of -2 is applied to horizontal movements made while the UAV is still below the designated cruise altitude. Together, these constraints condition the UAV to prioritize ascending vertically to a safe height before initiating horizontal travel toward the destination.

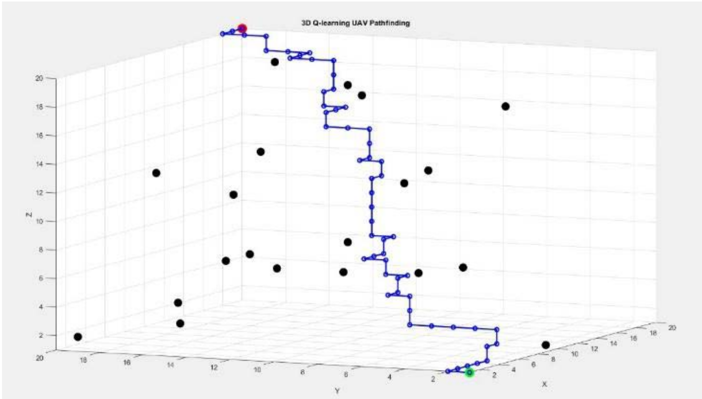

Figure 5. 3D Q-learning path planning

2.4 Operational System Development

The Operational System Development phase validates the transition from theoretical design to practical urban simulations. utilizing the A algorithm* for pathfinding and Euclidean distance monitoring for collision avoidance, the system successfully coordinates multi-UAV setups, as can be seen in Figure 6 and Figure 7. This phase ensures safe navigation around static and dynamic hazards (such as bad weather), proving the system's scalability and real-time decision-making capabilities.

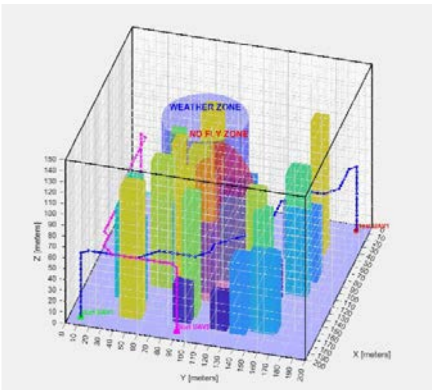

Figure 6. Path planned for 2 UAVs

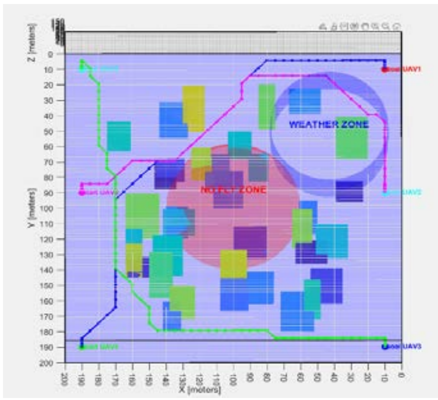

Figure 7. Path planned for 3 UAVs

2.5 Data Integration and Analytics

The data integration and analytics phase is critical for the safe and efficient operation of the UAV fleet by establishing a robust infrastructure for real-time data exchange between drones and cloud systems. At the core of this architecture is the Pixhawk Pro microcontroller, as shown in Figure 8, which collects telemetry data such as altitude and speed using the MAVLink protocol and integrates advanced sensors like GPS and LiDAR for enhanced navigation. To facilitate cloud connectivity, a Python script functions as a bridge, processing raw data and pushing updates every second to the Firebase Realtime Database, as shown in Figure 9, where information is organized into individual nodes to ensure the system remains scalable as more drones are added. This setup enables operators to monitor critical parameters continuously and make immediate, informed decisions like rerouting, ultimately supporting a user-friendly application for comprehensive fleet control.

Figure 8. Pixhawk Pro used for S-UFMC

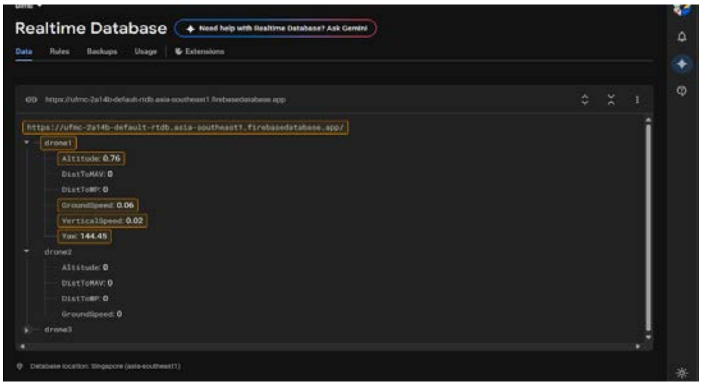

Figure 9. Real-time database in Firebase

2.6 Development of Application

The frontend of the S-UFMC is developed using React for its flexibility and real-time data integration with Firebase. The application provides a user-friendly dashboard that displays real-time telemetry data such as altitude, ground speed, yaw and vertical speed, with dynamic updates from Firebase. Pico.css is used for minimalistic styling, ensuring a clean and responsive design. Users can select individual UAVs to monitor, and data is visualized through gauges and progress bars for quick interpretation of key metrics. React's state management ensures real-time synchronization, allowing automatic updates of UAV data without page refresh.

3. RESULTS AND DISCUSSION

3.1 Operational System

The S-UFMC operates within a structured 3D grid-based airspace (U-Space), designed to simulate and manage complex urban UAV operations. This environment divides the airspace into a manageable cubic grid (e.g., 200x200x150m), which simplifies pathfinding and ensures predictable, safe navigation. This virtual space is populated with obstacles to test algorithm robustness, including randomly generated static obstacles like buildings (with safety margins) and dome-shaped No-Fly Zones, as well as dynamic obstacles like "Bad Weather Zones" that shift during flight to challenge the system's real-time adaptability.

The S-UFMC simulation is interactive and scalable. Users begin by selecting the number of UAVs they wish to simulate, either 1, 2, or 3 UAVs, as shown in Figure 10, 11 and 12 respectively, which then calls the appropriate function. After assigning start and goal stations for each drone, the system employs the A* algorithm to calculate an optimal flight path. This path is intelligently planned in three distinct phases: a vertical ascent to a safe cruising altitude, a horizontal path planned on a 2D grid, and a final descent to the goal, all while automatically routing around the static obstacles.

A key feature of the system is its management of dynamic hazards and multi-UAV deconfliction. To prevent inter-UAV collisions, the system continuously monitors the Euclidean distance between all drones. If any two UAVs breach a predefined safe distance of 5 meters, one is automatically paused until safe separation is restored. Furthermore, if a UAV's path intersects a "Bad Weather Zone," its mission is automatically halted to ensure safety. Users can monitor the entire operation via a real-time 3D animation with unique markers for each UAV and interactive controls to start or reset flights and receive a full flight summary and data log upon completion.

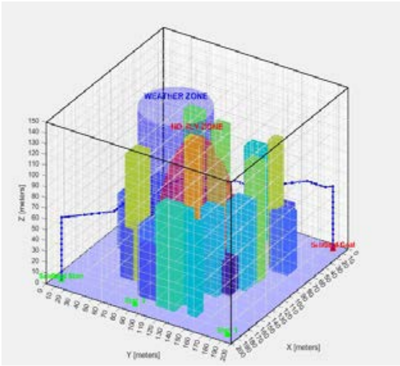

Figure 10. One-UAV system

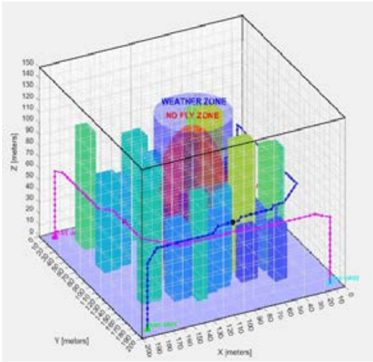

Figure 11. Two-UAV system

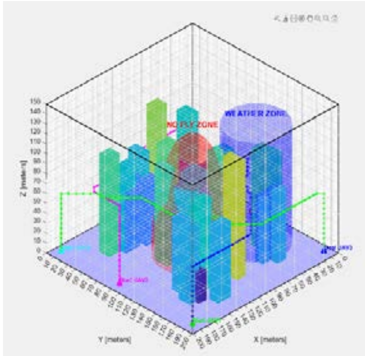

Figure 12. Three-UAV system

3.2 S-UFMC using Reinforcement Learning

This final simulation demonstrates 3D UAV path planning using RL, specifically the Q-learning algorithm, as shown in Figure 13. The system trains a UAV to autonomously navigate a 3D occupancy grid populated with randomly generated obstacles, like buildings. The UAV learns through trial and error by interacting with its environment, choosing from 26 possible 3D movements. Its decision-making is guided by a reward system that encourages moving closer to the goal and penalizes obstacle collisions or incorrect altitudes. The agent uses an epsilon-greedy strategy to balance exploring new actions with exploiting known good paths, improving its efficiency over time. Once training, like the one shown in Figure 14, is complete, the UAV utilizes its learned Q-table to find the optimal path from a start to a goal station. This final path and the UAV's autonomous decision-making process are then showcased in a 3D visualization with animations.

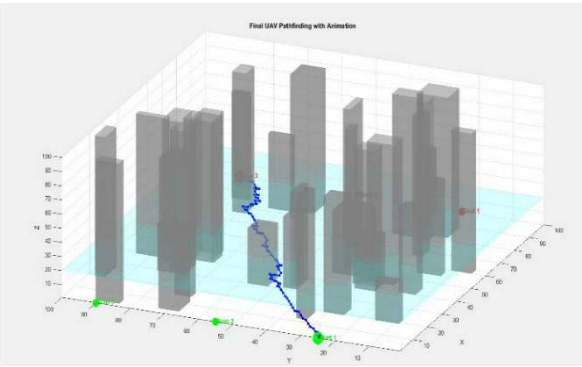

Figure 13. Q-learning for UAV path planning

```
Episode 1, Total Reward: -145566.54, Steps: 3000, Epsilon: 0.899
Episode 500, Total Reward: -4637.20, Steps: 351, Epsilon: 0.546
Episode 1000, Total Reward: -486.69, Steps: 209, Epsilon: 0.331
Episode 1500, Total Reward: -91.89, Steps: 151, Epsilon: 0.201
Episode 2000, Total Reward: 928.90, Steps: 120, Epsilon: 0.122
Episode 2500, Total Reward: 1264.80, Steps: 110, Epsilon: 0.074
Episode 3000, Total Reward: 1176.26, Steps: 117, Epsilon: 0.050
Episode 3500, Total Reward: 1138.31, Steps: 109, Epsilon: 0.050
Episode 4000, Total Reward: 1186.41, Steps: 117, Epsilon: 0.050
Episode 4500, Total Reward: 1276.44, Steps: 110, Epsilon: 0.050
Episode 5000, Total Reward: 1268.93, Steps: 112, Epsilon: 0.050
Episode 5500, Total Reward: 1040.85, Steps: 128, Epsilon: 0.050
Episode 6000, Total Reward: 1036.93, Steps: 114, Epsilon: 0.050
Episode 6500, Total Reward: 1068.93, Steps: 113, Epsilon: 0.050
```

Figure 14. Progression of RL during UAV path planning

3.3 Flight Log Summary

During the mission, the flight log captures detailed data, including the start and goal coordinates, the full path with all waypoints, velocity, total time, total path length and timestamps for each movement. This allows for a granular analysis of the UAV's progress and its behaviour when encountering obstacles or restricted zones. At the end of the mission, a summary as shown in Figure 15, provides a high-level overview of key performance indicators, such as mission completion status, total path length, total time taken and average velocity. Together with information such as safe distances to prevent collision between UAVs and command output as shown in Figure 16 and Figure 17, these metrics ensure transparency and allow for the optimization and safety of the mission to be evaluated by assessing the UAV's overall speed and efficiency.

```
UAV1 Arrived at Goal!
Start Coordinate: [190.00, 190.00, 0.00]
Goal Coordinate:  [10.00, 10.00, 0.00]
Total Path Length: 441.92 meters
Total Time Taken:  22.05 seconds
Average Velocity:  20.04 m/s
```

Figure 15. Summary of UAV mission

```
UAV3 waiting at step 299 to maintain safe distance from UAV1 and/or UAV2
UAV3 waiting at step 300 to maintain safe distance from UAV1 and/or UAV2
UAV3 waiting at step 301 to maintain safe distance from UAV1 and/or UAV2
UAV3 waiting at step 302 to maintain safe distance from UAV1 and/or UAV2
UAV3 waiting at step 303 to maintain safe distance from UAV1 and/or UAV2
UAV3 waiting at step 304 to maintain safe distance from UAV1 and/or UAV2
UAV3 waiting at step 305 to maintain safe distance from UAV1 and/or UAV2
UAV3 waiting at step 306 to maintain safe distance from UAV1 and/or UAV2
UAV3 waiting at step 307 to maintain safe distance from UAV1 and/or UAV2
UAV1 Arrived at Goal!
```

Figure 16. Sample of distance data

```
UAV2 mission halted due to bad weather conditions
```

Figure 17. Command output when mission is halted

3.4 IoT Data Visualization

The IoT dashboard, as shown in Figure 18, provides an intuitive interface for real-time visualization of telemetry data, such as altitude, ground speed, yaw and vertical speed, allowing operators to easily monitor drone performance. The dashboard fetches the latest data from Firebase, ensuring the interface is continuously updated with the most current information. A login page is integrated into the UAV Fleet Management and Control System, requiring user authentication with an email and password to prevent unauthorized access. Once authenticated, users can access the main interface to manage drone missions, view telemetry data, and oversee fleet operations, as can be seen in Figure 19. This integration of hardware, cloud storage, user authentication and a real-time dashboard facilitates secure remote monitoring and control of UAVs, providing a comprehensive solution for managing drone operations while ensuring that only authorized personnel can access sensitive data and controls.

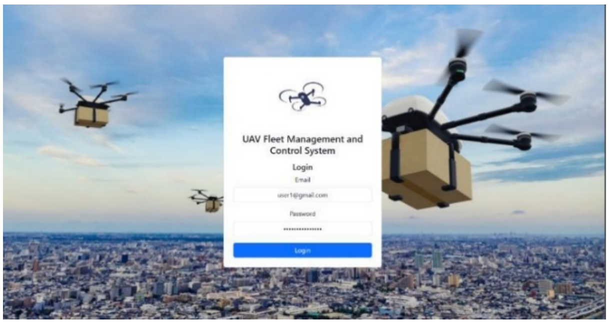

Figure 18. Login page to the IoT dashboard

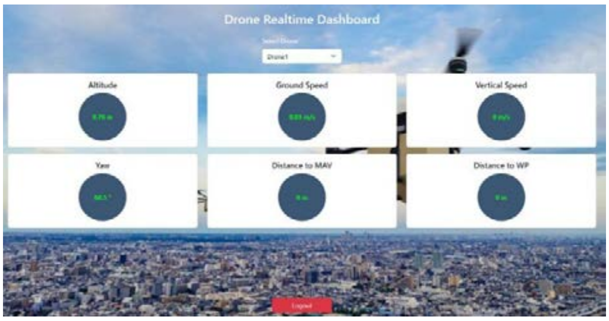

Figure 19. Data visualization of UAV

3.5 Comparative Analysis

The S-UFMC fundamentally transforms UAV operations by introducing a grid-based 3D U-Space architecture. This system moves beyond traditional planar navigation by segmenting the urban environment into volumetric corridors, allowing drones to utilize vertical space for more efficient trajectories. The operational superiority of the S-UFMC is driven by the synergistic integration of two distinct algorithms: the *A algorithm**, upgraded from a standard 2D implementation to a 3D solver for global route planning, and RL, specifically 3D Q-learning, for dynamic adaptability. Additionally, the system ensures scalability and safety through automated fleet management, integrating an IoT framework with cloud connectivity to transition isolated drone operations into a cohesive, monitored fleet.

A qualitative comparison between the A* algorithm and RL within the S-UFMC system reveals a distinct trade-off between immediate optimality and dynamic adaptability. A* serves as the "gold standard" for precision in static environments, mathematically guaranteeing the shortest path by calculating the lowest estimated total cost. This ensures strict adherence to constraints like cruising altitudes and no-fly zones. However, its rigidity becomes a limitation in dynamic settings, as it typically requires computationally expensive recalculations whenever environmental factors change. In contrast, RL excels in adaptability, empowering UAVs to make real-time, autonomous decisions in response to unpredictable stressors such as shifting weather patterns or sudden obstacles. While RL initially involves a learning curve characterized by suboptimal behaviours during early training episodes, it eventually converges on highly efficient navigation strategies through trial-and-error. Ultimately, the system benefits from a complementary approach, utilizing A* for reliable initial planning in known environments and RL for the intelligent, responsive handling of complex, high-density traffic scenarios where rule-based algorithms may fail.

The implementation of the S-UFMC creates a fundamental shift in operational capabilities when compared to traditional methods. In the absence of such a system, UAV operations often rely on two-dimensional path planning or manual piloting, treating airspace as a flat plane. This force drones to navigate the perimeter of obstacles rather than utilizing vertical space, leading to inefficient flight paths and increased energy consumption. Furthermore, coordinating multiple UAVs is hazardous due to the lack of real-time communication and separation monitoring, increasing the risk of mid-air collisions. These systems also lack dynamic adaptability, meaning UAVs on fixed routes cannot autonomously react to sudden environmental changes, often requiring human intervention to abort missions. With S-UFMC, these limitations are addressed by enabling drones to fly over low-rise buildings via the Z-axis, significantly optimizing trajectory efficiency. It ensures scalability and safety through automated fleet management, utilizing real-time telemetry and Euclidean distance monitoring to coordinate up to three UAVs simultaneously. By integrating an IoT framework, the system allows for immediate ground-control decision-making and the seamless integration of new flight units into the existing traffic flow, ensuring robust navigation in complex, high-density urban settings.

4. CONCLUSION

The S-UFMC has successfully establishes a robust framework for optimizing UAV operations in complex urban environments. By integrating RL, a grid-based 3D airspace model and real-time IoT protocols like MQTT, the system significantly improves pathfinding efficiency, dynamic obstacle avoidance and fleet synchronization. MATLAB simulations validated the system's effectiveness, demonstrating that RL-trained UAVs can navigate dynamic challenges such as no-fly zones and adverse weather.

However, the system is primarily limited as a simulation-based proof of concept without real-world hardware validation against physical factors like sensor noise. Computational constraints restricted scalability to only three UAVs, preventing assessment of high-density traffic management. Navigational precision is currently limited by 8-directional movement rather than a more complex 26-directional model, and the airspace model needs refinement for cluttered urban settings. Future work should focus on scaling to larger fleets, enhancing movement precision, migrating to advanced simulators like AirSim or Gazebo and addressing low-latency communication challenges for real-world deployment.

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