

Network Congestion-aware Path Planning for Indoor Multi-UAV Systems

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Abstract—Indoor multi-UAV systems have a variety of applications including for warehouse logistics, security and safety. Operating over Wi-Fi networks, such systems face network QoS challenges owing to congestion, interference, and varying traffic demands. However, they offer a distinct private network operating environment, in which a high degree of control over the number of active UAVs, their movement and their generated data traffic can typically be assumed. This research presents a novel communication-aware path-planning model for indoor multi-UAV Wi-Fi networks, where the mobility and AP-association decisions of each UAV influence the throughput and QoS experienced by other UAVs. A multi-agent path planning algorithm is developed in which UAV flight paths are planned in sequence, each using the A* algorithm to avoid previous UAVs and areas with high channel contention. The A* cost function incorporates three objectives: path length, QoS, and handover count, balancing travel efficiency against communication performance. The algorithm makes use of a detailed 3D map, containing empirical measurements of observed throughput and recorded RSSI values. The proposed algorithm was evaluated using ns-3 simulations and compared with a number of alternatives (Euclidean, Greedy QoS, and A* RSSI Aware), demonstrating its effectiveness in balancing QoS and path efficiency. Simulation results demonstrate that the proposed PQH A* algorithm improves QoS compared to the other evaluated approaches. In addition, unnecessary AP handovers and outage duration are significantly reduced, leading to more stable network operation, lower signaling overhead, and improved overall communication reliability.

Index Terms—Indoor UAVs, Multi-UAVs, Edge Computing, WiFi resource Management, Path planning

I. INTRODUCTION

The deployment of lightweight Unmanned Aerial Vehicles (UAVs) in indoor environments has attracted significant attention in academia and industry. This rapid progress is driven by their autonomous capabilities, agility, cost-effectiveness, and suitability for operation in GPS-denied environments. Owing to their compact size and autonomous navigation capabilities, UAVs can operate safely in confined and infrastructure-rich indoor spaces [1]. When deployed as coordinated multi-UAV systems, they enable parallel task execution, faster area coverage, improved operational efficiency, and enhanced performance. Consequently, multi-UAV systems are increasingly used in applications such as logistics, warehouse automation, industrial inspection, surveillance, underground exploration, and infrastructure monitoring [2]–[4].

Indoor multi-UAV systems commonly rely on IEEE 802.11 WLAN technologies because of their low deployment cost, high throughput, ease of integration, and compatibility with real-time telemetry and video transmission [5]. In practical deployments, UAVs frequently transmit high-volume sensory data, particularly real-time video streams, to edge servers or ground control stations (GCS) for video and data processing and decision-making. To meet strict latency requirements and cope with dynamically changing links, such data are typically transmitted using UDP-based communication, which avoids retransmission delays but lacks built-in congestion control, unlike TCP. Although modern Wi-Fi technologies (e.g., IEEE 802.11ac/ax) offer high theoretical data rates, with the effective throughput limited by shared medium access, protocol overhead, interference, and contention among multiple devices. Unlike low-rate command-and-control traffic, a single UAV streaming real-time 4K video may require up to 40–50 Mbps [6]. Therefore, multiple UAVs transmitting simultaneously through the same Wi-Fi AP can easily exceed the practical AP capacity, causing congestion and QoS degradation. This lack of control of QoS can have potentially catastrophic implications for some types of Indoor UAV applications.

The main contributions of this research are summarized as follows:

- We present a novel communication-aware path-planning model for indoor multi-UAV Wi-Fi networks, where the mobility and AP-association decisions of each UAV influence the throughput and QoS experienced by other UAVs due to shared-medium contention and airtime competition. Unlike existing communication-aware UAV path-planning approaches that rely on static communication maps, RSSI/SINR thresholds, or independent link assumptions, the proposed framework explicitly models the coupled interaction between UAV mobility, AP load, congestion, and QoS degradation in indoor Wi-Fi environments.
- A key contribution of this work is the development of a multi-objective A*-based algorithm (called PQH A*) for indoor multi-UAV path planning that jointly considers path length, QoS, and AP handovers under shared Wi-Fi resource constraints. Conventional approaches relied only on geometric distance or static communication

metrics, while the proposed formulation combines an empirical throughput map with a congestion-aware QoS estimation based on AP load and airtime sharing among UAVs. The cost function enables UAVs to avoid congested regions, maintain a higher QoS, and reduce unnecessary handovers while preserving efficient path trajectories.

- We evaluated the multi-UAV path planning using heuristic algorithm using ns-3 simulations and MATLAB for Wifi-6 network configurations where multi-UAV scenarios shared Wi-Fi access points. The proposed communication-aware approach was compared with conventional Euclidean distance path planning, RSSI-aware path planning, and greedy QoS-aware methods. The results demonstrate improved QoS satisfaction and reduced outage events, validating the effectiveness of the proposed congestion-aware framework for indoor multi-UAV operations.

II. RELATED WORK

Existing research on communication-aware UAV systems has primarily focused on trajectory optimization under connectivity, coverage, or SINR/RSSI constraints, primarily in cellular network environments and outdoor scenarios. A significant portion of the literature employs graph-based methods, such as modified A*, weighted A*, and variants of Dijkstra's algorithm, to generate connectivity-aware paths while balancing trade-offs between path length and communication reliability [7]–[10]. Reliability here usually means maintaining network coverage or a minimum signal strength.

In addition, optimization-based techniques, including successive convex approximation (SCA), dual decomposition, and mixed-integer linear programming (MILP), have been applied to jointly optimize UAV trajectories and communication resources. Recently, learning-based approaches such as deep reinforcement learning (DRL), including Dueling DDQN and multi-step learning frameworks, have been explored to dynamically adapt UAV trajectories under connectivity and outage constraints. Furthermore, multi-UAV coordination problems have been addressed using techniques such as mTSP formulations, NSGA-II optimization, and event-driven replanning strategies to ensure connectivity and mission completion [11]–[19]. Most of these approaches rely on static or precomputed communication maps, binary connectivity thresholds, or simplified QoS representations. A limited number of studies consider bandwidth awareness or communication quality; however, they typically assume isolated links and do not capture interactions among multiple UAVs competing for shared wireless resources and competing with other cellular users. Our prior work examined the opportunity for dynamically adapting traffic for UAVs so as to improve overall QoS. Recent studies investigated congestion control and fairness optimization in Wi-Fi networks using congestion-aware scheduling and deep reinforcement learning approaches [20]–[22]. However, these works do not address communication-aware path planning and QoS-constrained

mobility for indoor multi-UAV systems. Our previous work [23] proposed an edge-computing-based congestion control framework for indoor multi-UAV networks, while this work extends it with prioritized multi-agent planning [24] using communication-aware timed A* as the central algorithm.

Although the existing literature provides valuable insights into communication-aware UAV path planning, most studies are designed for outdoor or cellular-connected environments and do not reflect the operating realities of indoor wireless networks. Approaches relying only on RSSI, SINR, or coverage maps fail to capture the dominant QoS factors. Existing methods also rely on offline or periodic replanning and lack potential to provide dynamic adaptation to real-time QoS degradation, RSSI drops, and AP congestion. Finally, the controlled nature of the indoor environment that would be common in multi-UAV deployments provides an opportunity for resource allocation planning that is outside the scope of prior work on outdoor UAV networking.

III. PROBLEM FORMULATION AND SYSTEM MODEL

A. Problem Formulation

In the proposed indoor environment, N UAVs communicate with M Wi-Fi access points (APs), where each UAV u_i is associated with one AP a_j at any given point in time. Owing to the shared nature of the Wi-Fi medium, multiple UAVs connected to the same AP contend for limited wireless resources, potentially leading to congestion and degradation of QoS. Each UAV generates traffic with a required data demand D_i , and the achievable throughput is denoted by T_i . The QoS of UAV i is defined as $QoS_i = \min\left(1, \frac{T_i}{D_i}\right)$, and it must satisfy $QoS_i \geq \delta$, where δ is the minimum required QoS. The total load at AP a_j is given by $L_j = \sum_{u_i \in \mathcal{U}_j} R_i$, where R_i is the transmission rate allocated to UAV u_i . Congestion occurs when multiple UAVs demand high data rates while being associated with the same AP, causing throughput degradation, even under strong signal conditions. The wireless link quality between UAV u_i and AP a_j is characterized by the received signal strength $RSSI_{i,j}$, which depends on the UAV position and indoor propagation conditions. UAV mobility introduces

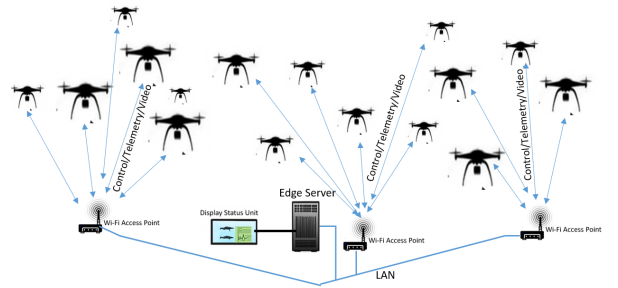


Fig. 1: System Model with UAVs, Wi-Fi Access Point and an Edge Server

dynamic variations in both the RSSI and AP load, resulting in time-varying and coupled network behavior across all UAVs. To sustain network performance and avoid congestion, the

edge controller adjusts the AP associations α_i based on the current network conditions via a path planning algorithm. The goal is to maintain the QoS of all UAVs above the required threshold while mitigating the congestion effects in the shared Wi-Fi environment. This formulation captures the key challenge of jointly managing wireless resource allocation and AP association in indoor multi-UAV networks under fixed-traffic and mobility conditions.

B. System Model

The considered system consists of an indoor multi-UAV network with a set of UAVs $\mathcal{U} = \{u_1, \dots, u_N\}$, a set of Wi-Fi access points (APs) $\mathcal{M} = \{a_1, \dots, a_M\}$. UAVs operate in a confined indoor environment and communicate with the CNC through APs using *UDP-based traffic*, which is typically used for real-time video streaming and telemetry. UAVs are mobile, resulting in dynamic variations in link quality, interference, and AP load over time, as shown in Fig. 1.

1) *3D Indoor Grid Representation and UAV Motion Model*: The indoor environment is modeled as a bounded 3D space $\Omega = [0, L] \times [0, W] \times [0, H]$ and discretized into uniform cubic voxels with side length I . A voxel center representation is adopted, where each node corresponds to the center of a voxel, that is, $\mathbf{p}(i, j, k) = [(i - \frac{1}{2})I, (j - \frac{1}{2})I, (k - \frac{1}{2})I]^T$. The resulting grid forms a graph $G = (\mathcal{V}, \mathcal{E})$, where the nodes denote the voxel centers and the edges represent feasible transitions. The UAV state evolves as $Z_{t+1} = Z_t + a_t$, where $a_t \in \mathcal{A}$. A 26-neighbor motion model is used, where $\mathcal{A} = \{(\Delta x, \Delta y, \Delta z) \in \{-1, 0, 1\}^3 \setminus (0, 0, 0)\}$, enabling face, edge diagonal, and body diagonal moves. The transition cost is defined by the Euclidean distance, that is, I , $\sqrt{2}I$, and $\sqrt{3}I$ for the respective moves. A feasible path $P = \{Z_1, \dots, Z_S\}$ satisfies $Z_{t+1} \in \mathcal{N}(Z_t)$. This formulation ensures geometrically consistent and flexible 3D UAV navigation suitable for graph-based planning.

2) *UAV Model*: Each UAV u_i generates traffic with demand D_i and is assigned a transmission rate R_i . The achieved throughput is denoted by T_i , and the communication performance is quantified as

$$QoS_i = \min \left(1, \frac{T_i}{D_i} \right). \quad (1)$$

Each UAV is associated with an AP $\alpha_i \in \mathcal{M}$ and periodically reports its measured throughput T_i , received signal strength $RSSI_{i,j}$. The UAVs position $\mathbf{p}_i$ directly affects the RSSI and interference, and owing to mobility, both the link conditions and network load vary dynamically.

3) *Access Point Model*: Each AP a_j operates on a non-overlapping Wi-Fi channel and has a finite capacity C_j . UAVs associated with AP a_j form a set $\mathcal{U}_j$, and the total load is given by

$$L_j = \sum_{u_i \in \mathcal{U}_j} R_i. \quad (2)$$

Owing to the contention-based medium access in Wi-Fi, the throughput experienced by each UAV depends not only on the RSSI but also on the number of competing UAVs and their

traffic demands. As the load L_j increases, contention leads to a reduced throughput and QoS degradation.

4) *Assumptions for Indoor Environment*: The indoor environment represents a controlled indoor setting, such as a smart warehouse or industrial factory, where UAVs operate within a bounded three-dimensional space. The network environment is controlled, and without permission, users cannot use indoor wireless APs. All UAVs are assumed to be identical in terms of communication hardware, antenna configuration, transmission power, and processing capability, ensuring homogeneous and fair network behavior. Each UAV operates autonomously and follows the trajectories generated by the algorithms. UAVs are not operated in uncovered coverage areas, and the final position of the UAVs is in the coverage areas. The presence of obstacles such as shelves, machinery, walls, and metallic structures introduces multipath propagation, shadowing, and attenuation. Additionally, electromagnetic noise from industrial equipment can affect the signal quality, leading to localized variations in the communication performance. To evaluate the wireless link quality, key physical-layer metrics, including the RSSI, SNR, and SINR, are considered. The RSSI represents the received signal power at the UAV and is measured at the receiver based on the packet reception strength. The SNR is computed as the ratio between the received signal power and background noise, reflecting the link quality under noise-limited conditions. SINR further incorporates interference from other UAVs sharing the same wireless medium, making it a more realistic indicator of multi-UAV Wi-Fi networks. These metrics may exhibit short-term fluctuations owing to multipath effects, interference, and contention. Therefore, RSSI, SNR, SINR, and throughput were measured over observation intervals and averaged to obtain stable and representative values, ensuring a reliable evaluation of QoS and congestion control performance.

IV. COMMUNICATION-AWARE A* PATH PLANNING AND COST FUNCTION DEVELOPMENT

The UAV trajectory is optimized using a multi-objective cost function:

$$J = w_1 J_{\text{len}} + w_2 J_{\text{QoS}} + w_3 J_{\text{HO}}, \quad (3)$$

where J_{len} , J_{QoS} , and J_{HO} represent path efficiency, communication quality, and handover cost, respectively. All cost-function parameters ($w_1, w_2, w_3 = [0.3, 0.3, 0.3]$, $\delta = [0.3]$, $RSSI_{\text{min}} = [-81 \text{ dBm}]$, $v_{\text{max}} = 1 \text{ m/s}$, $I = 1 \text{ m}$, $D_{\text{max}} = [30 \text{ Mbps}]$) will be added as a table in the revised manuscript.

1) *Path Length Cost*: The path-length cost represents the total traveled distance along the actual algorithm-generated UAV trajectory in the 3D indoor grid. It is computed by summing the Euclidean distance between consecutive waypoints along the planned path. Since the framework uses a 26-neighbor motion model, the movement cost depends on the selected motion direction and may correspond to face, edge-diagonal, or body-diagonal movements.

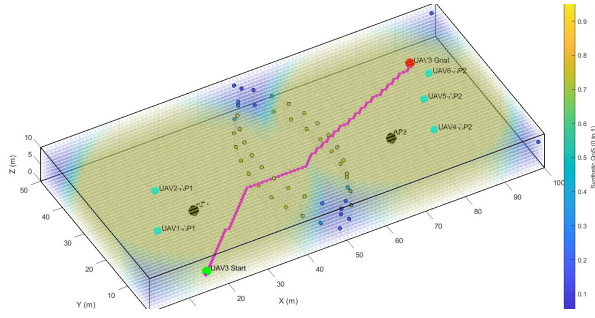


Fig. 2: Indoor UAVs Throughput Map

$$J_{\text{len}} = \sum_{k=1}^{N_p} \|x_k - x_{k-1}\|_2 \quad (4)$$

where

$$\|x_k - x_{k-1}\|_2 \in \{I, \sqrt{2}I, \sqrt{3}I\}$$

depending on the selected UAV motion action.

2) *QoS-Based Cost*: To model communication quality, an empirical baseline throughput map $T_{\text{base}}(x, j)$ is constructed by measuring the achievable throughput from access point (AP) j across the environment for a single UAV as shown in Fig. 2. This map captures realistic indoor propagation effects such as path loss, fading, and blockage. For multi-UAV scenarios, airtime fairness is assumed, where the available throughput is equally shared among UAVs connected to the same AP. Airtime fairness was adopted as a lightweight approximation of practical Wi-Fi medium sharing behavior under saturated traffic conditions. The effective throughput for UAV i at location x_k is therefore given by

$$\hat{T}_i(x_k, j) = \frac{T_{\text{base}}(x_k, j)}{n_j^{(+i)}}, \quad (5)$$

This map is then used as a heuristic estimate of the expected communication performance during path planning. where $n_j^{(+i)}$ denotes the number of UAVs associated with AP j . The normalized QoS metric is defined as

$$QoS(x_k, j) = \frac{\hat{T}_i(x_k, j)}{D_{\text{max}}}, \quad (6)$$

and the corresponding QoS cost is

$$J_{\text{QoS}} = \sum_{k=1}^{N_p} \max(0, \delta - QoS(x_k, j)). \quad (7)$$

This formulation penalizes low-throughput regions and drives the UAV toward areas with higher QoS, effectively avoiding congestion and weak communication zones.

3) *Handover Cost*: The handover cost is defined as

$$J_{\text{HO}} = \sum_{k=1}^{N_p} \mathbb{I}(\alpha(k) \neq \alpha(k-1)), \quad (8)$$

where $\alpha(k)$ denotes the serving AP at step k . This term counts the number of AP switching events along the trajectory.

Minimizing it reduces frequent handovers, thereby improving connection stability and reducing signaling overhead and packet loss.

4) *Feasibility Constraints*: The planned trajectory must satisfy communication and motion constraints:

$$RSSI(x_k, j) \geq RSSI_{\text{min}}, \quad QoS(x_k, j) \geq \delta, \quad (9)$$

$$x_k \in \mathcal{V}_{\text{free}}, \quad \|x_{k+1} - x_k\|_2 \leq v_{\text{max}} \Delta t. \quad (10)$$

These constraints ensure that the UAVs remain connected to the network, achieves the required QoS, avoids obstacles, and follows physically feasible motion. Together, the proposed formulation enables communication-aware trajectory planning that jointly optimizes mobility and network performance.

V. MULTI-UAVS PATH PLANNING ALGORITHM

The proposed framework introduces a communication-aware PQH A* path-planning heuristic algorithm for co-ordinated indoor multi-UAV operations under shared Wi-Fi communication constraints. The proposed heuristic algorithm jointly considers UAV mobility, wireless communication quality, AP congestion, and AP handover during the planning process. The algorithm begins by collecting global network and environmental information, including UAV states, AP load maps, RSSI maps, throughput maps, obstacle maps, and UAV traffic demands.

A. Algorithm Working and Flow

The proposed algorithm for multi-UAV path planner jointly considers UAV mobility and wireless network conditions during A* path planning. The input `UAVStates` stores the state of all UAVs, including UAV ID, initial position $start_i$, final destination $goal_i$, current AP association, movement state, and transmission requirement. The input `APLoads` stores the current congestion level of each access point based on the number of connected UAVs and their transmission rates, while `ThroughputMap` provides the predicted achievable throughput at each 3D voxel location for different APs. The input `UAVDemands` stores the required data-rate demand of each UAV and is used to calculate the QoS. The algorithm outputs `TimedSequencePlannedUAVpaths`, which contains the final timed UAV trajectories, `ReservationTable`, which stores reserved space-time path entries of successfully planned UAVs, `AllowedUAVSet`, which contains UAVs with feasible collision-free and QoS-valid paths, and `BlockedUAVSet`, which contains UAVs that cannot be planned due to obstacles, path conflicts, congestion, or QoS violations. During planning, the algorithm initializes helper data structures such as the `frontier`, `MeasuredLoadMap`, and `MeasuredQoSMap`. The `frontier` is the A* priority queue that stores candidate nodes, while `closed` stores already explored nodes.

Algorithm 1 Communication-Aware Multi-UAV A* Path Planning

Input: UAVStates, APLoads, ThroughputMap, UAVDemands

Output: TimedSequencePlannedUAVpaths, ReservationTable, AllowedUAVSet and BlockedUAVs

```

1 Initialize ReservationTable, MeasuredLoadMap, MeasuredQoSMap Initialize
  AllowedUAVSet, BlockedUAVSet, closed and frontier
  // PQH A* Cost Function: The cost function is defined
  as  $f(n) = g(n) + h(n) + \lambda_1 C_{QoS} + \lambda_2 C_{handover}$ , where
   $g(n)$  is the accumulated path cost from the start node
  to the current node,  $h(n)$  is the heuristic distance
  from the current node to the goal,  $C_{QoS}$  is the QoS
  penalty, and  $C_{handover}$  is the AP handover penalty.
  The weighting factor  $\lambda_1$  controls the importance of
  maintaining high QoS, while  $\lambda_2$  controls the importance
  of reducing unnecessary AP switching.
2 foreach UAV  $u_i$  do
3   found  $\leftarrow$  FALSE
4   frontier  $\leftarrow \{((start_i, 0), 0)\}$ 
5   while frontier is not empty do
6     curr  $\leftarrow$  frontier.remove_lowest() // curr = ((loc, time), cost)
7     closed.add(curr) // Mark node as explored
8     if curr.loc == goal then
9       found  $\leftarrow$  TRUE
10      Break // Exit search loop
11    end
12    children  $\leftarrow$  curr.loc.get_neighbors()
13    for c in children do
14      if c  $\notin$  closed and no physical conflicts then
15        Compute load of APs using MeasuredLoadMap
16        // Estimate congestion for each AP
17        Compute airtime fairness of APs // Refer to Eq 5
18        Estimate throughput of  $u_i$  at APs using ThroughputMap
19        // Predict achievable throughput per AP
20        Update predicted throughput for  $u_i$  and all UAVs associated with
        APs // impact on previously planned UAVs
21        if predicted QoS of  $u_i$  < threshold or predicted QoS of any
        previously planned UAV drops < threshold then
22          reject c and continue // Node fails QoS
        constraint
23        end
24        AP  $\leftarrow$  arg maxap QoS(c, ap) // Determine best AP
        at node c by QoS
25        if QoS remains above threshold then
26          c.g  $\leftarrow$  curr.g + dist(c.loc, curr.loc) // Update
        path cost
27          c.time  $\leftarrow$  round(c.g/vUAV) // Arrival time
        derived from accumulated path cost
28          c.h  $\leftarrow$  dist(c.loc, goal) // Heuristic distance
        to goal location
29          if (c.loc, c.time)  $\notin$  frontier or c.f <
        frontier.cost(c.loc, c.time) then
30            frontier.add((c.loc, c.time), c.f) // Add
        child to frontier if not yet
        visited or if a lower cost path is
        found
31          end
32        end
33      end
34    end
35  end
36  if found == TRUE then
37    path  $\leftarrow$  construct_path(ReservationTable) // Generate final path
38    for UAV  $u_i$ 
39      TimedSequencePlannedUAVpaths.add(path) // Store timed path
        sequence
40    Update ReservationTable with path // Reserve paths
41    Update Global AP load map with path
42    Update PredictedQoSMap with path
43    AllowedUAVSet.add( $u_i$ )
44  end
45  else
46    BlockedUAVSet.add( $u_i$ )
47  end
48 end
49 return TimedSequencePlannedUAVpaths, Reserva-
  tionTable, AllowedUAVSet, BlockedUAVSet

```

For each UAV u_i , the planner inserts the timed start node $((start_i, 0), 0)$ into the frontier and repeatedly se-

lects the node with the minimum communication-aware cost $f(n)$. For each child node c , the planner checks motion constraints, obstacle constraints, and path conflicts using the ReservationTable. It then measures AP association, selecting the AP with the highest QoS, estimates AP load and airtime fairness, predicts throughput using the ThroughputMap, and computes $QoS = Throughput/Demand$. Before accepting a node, the planner verifies that the QoS of the current UAV remains above the required threshold and that the QoS of all previously planned UAVs is not degraded by the new association. Only if both conditions are satisfied is the node accepted and added to the frontier; otherwise, it is rejected. Once a valid path reaches the goal, the timed path is reserved in the ReservationTable so that later UAVs cannot occupy the same voxel at the same time, thereby preventing collisions, overlapping trajectories, and unsafe multi-UAV movements. The corresponding QoS values are then recalculated and incorporated into the updated map.

VI. SIMULATIONS AND RESULTS

A. Configurations

In this research, the ns-3 network simulator is used to implement and evaluate the proposed congestion-aware path planning under various indoor multi-UAV scenarios with mobile UAVs. The simulations analyze how UAV planned paths influence throughput-based QoS. Network settings such as Wi-Fi standard, channel width, path loss model, and data rate were configured as specified in Table I.

B. Comparison Algorithms

To evaluate the performance of the proposed communication-aware algorithm, three baseline path planning algorithms are considered: Euclidean Path Planning, Greedy QoS Navigation, and RSSI-Aware A* Path Planning. Each baseline algorithm plans paths for each UAV independently, without awareness of other UAVs in the airspace.

1) *Euclidean Path Planning*: The Euclidean method generates the shortest straight-line path between the UAV start and goal positions without considering communication conditions, AP congestion, RSSI, or QoS constraints. The UAV continuously follows the minimum geometric distance trajectory, which provides the shortest travel time but may cause severe QoS degradation and communication outages in congested indoor Wi-Fi environments.

2) *Greedy QoS Navigation*: The Greedy QoS algorithm selects the next UAV waypoint based on local communication quality by prioritizing candidate positions with higher QoS values while also considering the remaining distance to the destination. Initially, the UAV defines its start position, goal position, speed, and maximum allowed mission time. During navigation, neighboring candidate positions are generated around the current UAV location while invalid and previously visited positions are removed to avoid loops and unnecessary movements. For every candidate waypoint, the algorithm estimates QoS and distance-to-goal, and computes a greedy

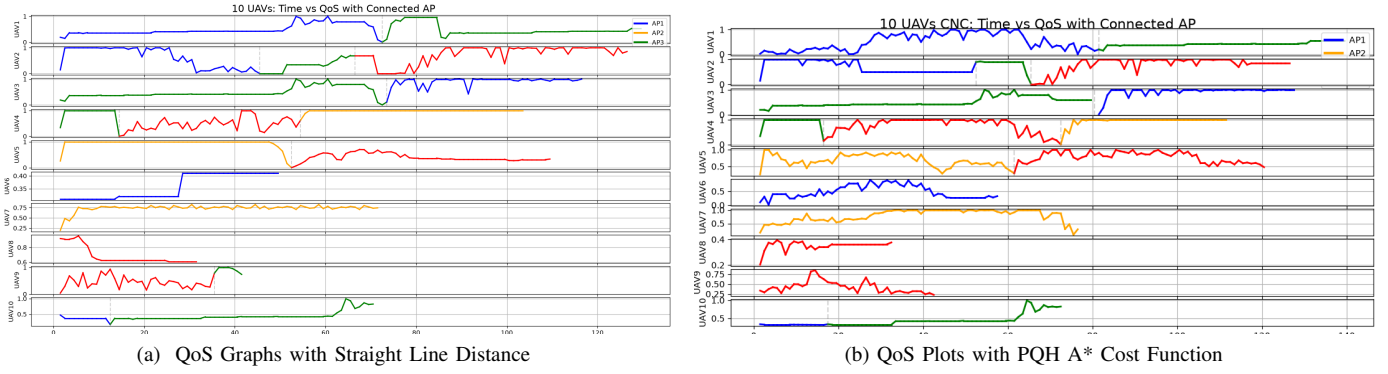


Fig. 3: Results with 4 APs and 10 UAVs with Euclidean and PQH A*

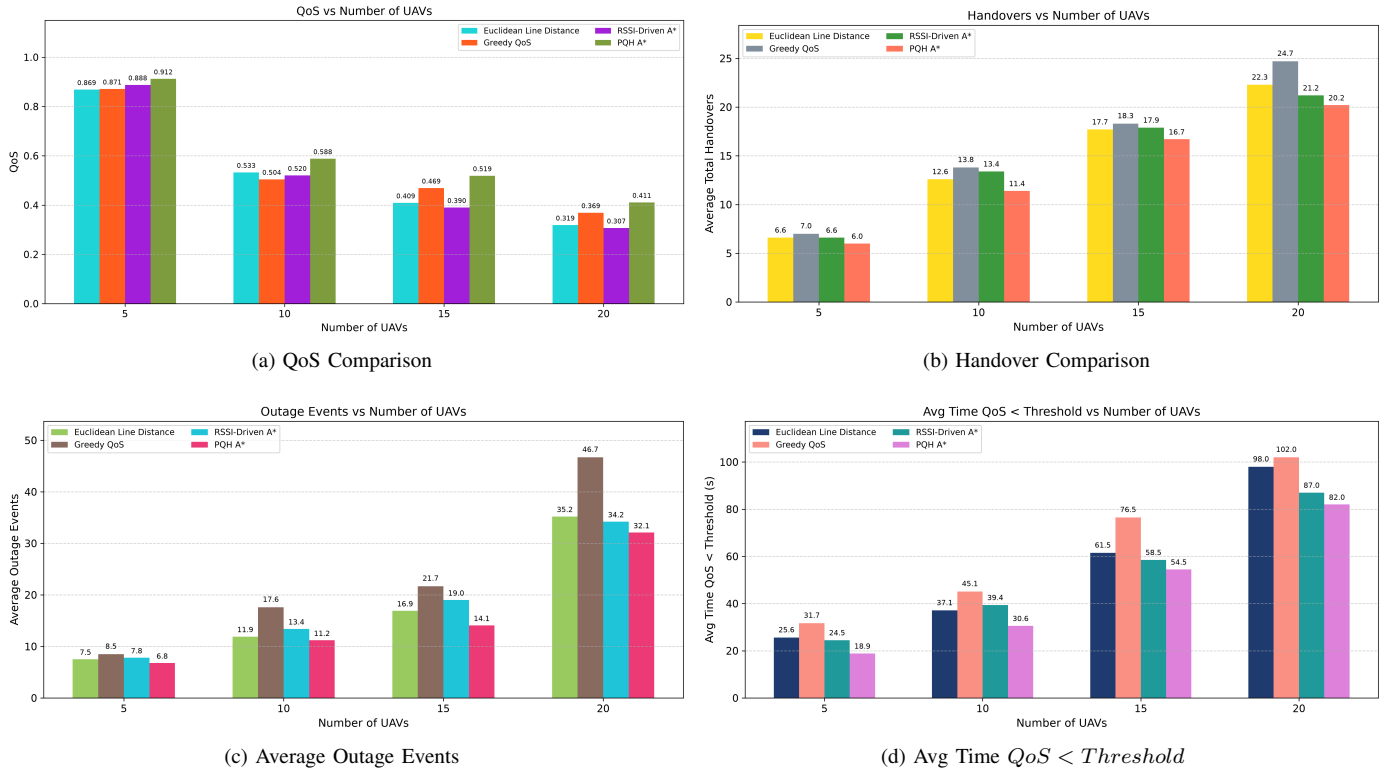


Fig. 4: Performance comparison between Euclidean Distance, QoS, A* RSSI Driven and PQH A*

score using equal weighting factors for all parameters. In this algorithm, each parameter was assigned an equal weight of approximately 0.33 (33%). The UAV then selects the candidate with the highest greedy score and updates its waypoint path, traveled distance, and elapsed mission time. If the remaining mission time becomes critically close to the minimum required direct-flight time, the algorithm disables QoS optimization and forces direct Euclidean movement toward the destination to guarantee mission completion.

3) *RSSI-Aware A* Path Planning*: The RSSI-Aware A* algorithm extends the conventional A* search method by incorporating RSSI measurements into the path planning cost function. Instead of minimizing only geometric distance,

the planner also favors paths passing through regions with stronger wireless signal strength. The algorithm searches globally over the voxel-based indoor map of RSSI measurements while considering both path length and communication quality, resulting in more reliable connectivity and reduced communication outage probability compared with purely geometric planning methods.

C. Performance Comparison and Analysis

The performance of the proposed framework was evaluated through network simulations across a set of scenarios. Each simulation scenario was executed using 10 independent random seeds in ns-3 to account for variability in mobility and

TABLE I: Configuration of Simulations

Sr.No	Parameter	Value
1	WiFi Standard	WiFi 6 (IEEE 802.11ax)
2	Path Loss Model	YansWifiChannel
3	MAC Rate Control	MinstrelHtWifiManager
4	Channel Settings	Bandwidth: 160 MHz/5 GHz
5	Modulation & Coding Scheme	Adaptive
6	Traffic Type	UDP
7	Peak Data Rate	30 Mbps
8	Area	200 Square Meter
9	Simulation Time	30 seconds to 3 minutes
10	UAVs Allocation	Mobile
11	Number of Mobile UAVs	5-20
12	AP Coverage Range	Up to 50 meters
13	Velocity of Mobile UAVs	1 m/s

the wireless-channel quality. For each seed, the experiment was repeated for each of the four algorithms. The evaluation considered key performance metrics, including path length, QoS achieved, AP load distribution, number of handovers, QoS outage duration, and mission completion time. The proposed PQH A* approach was compared with three baseline strategies: Euclidean path planning, QoS-greedy, and RSSI-aware methods, which are described in the previous subsection.

These baseline algorithms produce plans that may cause physical collisions, which are handled reactively by the simulation. Any UAV that encounters a conflicting node occupancy — where two UAVs would occupy the same 3D voxel at the same time — is delayed by 11.1 second at that point, forcing it to wait while the conflicting UAV clears the node before resuming its planned path. In contrast, the proposed PQH A* algorithm enforces collision-free multi-agent planning proactively. A deadlock detection mechanism was implemented, but no deadlock was encountered during the experiments. In the first method, UAVs follow Euclidean-based shortest paths, which results in minimal path length but leads to degraded QoS while following this path. This causes significant QoS degradation and increased contention, despite favorable RSSI conditions. In the second method, the QoS-based approach improves communication quality by steering UAVs toward higher-throughput regions; however, it often produces longer paths and increases the number of handovers, leading to inefficiencies and instability in the network association. The third method is RSSI aware, in which UAVs remain close to higher RSSI from the APs but are unaware of implications for QoS. In contrast, the proposed PQH A* algorithm jointly optimizes path planning, QoS, and AP association. By incorporating a multi-objective cost function, the framework effectively balances path length and communication performance requirements. As demonstrated in the results, the PQH A* approach achieves higher average QoS while significantly reducing QoS outage events for the UAVs. To further illustrate this effect, a representative QoS test case is presented in Fig. 3, which visually compares the performance of 10 UAVs using the Euclidean approach and the proposed PQH A* method. In addition, Fig. 4 presents

the overall performance comparison of all evaluated methods against the proposed PQH A* approach in terms of QoS and AP handovers.

The results demonstrate that the proposed PQH A* algorithm consistently achieves higher QoS performance compared to the Euclidean, Greedy QoS, and RSSI-Driven approaches under increasing network congestion. The overall comparison is presented in Table II for all multi-UAV mobile scenarios and planning methods. For the high-density scenario with 20 UAVs, the PQH A* method achieves a QoS value of 0.411, compared to 0.319 for the Euclidean method, 0.369 for the Greedy QoS method, and 0.307 for the RSSI-Driven approach. This corresponds to QoS improvements of approximately 29% over the Euclidean method, 11% over the Greedy QoS method, and 34% over the RSSI-Driven approach. Similarly, in the moderate congestion scenario with 15 UAVs, the PQH A* framework achieves a QoS value of 0.519, providing improvements of about 27%, 11%, and 33% over the Euclidean, Greedy QoS, and RSSI-Driven methods, respectively. The proposed PQH A* framework also significantly reduces outage events and QoS deficit duration. In the 10-UAV scenario, outage events are reduced from 17.6 and 13.4 for the Greedy QoS and RSSI-Driven methods to only 11.2 using PQH A*. Similarly, the QoS deficit duration decreases from 41.3 s and 33.8 s to 29.1 s. Furthermore, the average time spent below the QoS threshold confirms this trend: with 20 UAVs, PQH A* records only 82 s compared to 98 s for Euclidean, 102 s for Greedy QoS, and 87 s for the RSSI-Driven method, representing reductions of up to 20% over the weakest baseline. Overall, the results confirm that the proposed approach outperforms the baseline methods by providing a balanced trade-off between path efficiency and communication performance.

VII. CONCLUSION

This study presented a communication-aware and QoS-aware path planning algorithm for congestion management in indoor multi-UAV Wi-Fi networks. The proposed approach jointly optimizes UAV path planning, QoS, and AP association to improve communication performance while maintaining efficient and reliable UAV navigation in congested indoor environments. A unified multi-objective cost function based on the proposed PQH A* formulation was developed, which jointly incorporates path efficiency, QoS, and handover minimization. To capture realistic indoor wireless behavior, an empirical throughput map was used to reflect contention and shared medium effects. The simulation results demonstrated improved QoS satisfaction, reduced congestion, and more balanced AP utilization compared with the baseline approaches. In future work, this framework will be extended by incorporating adaptive UAV speed control to better respond to dynamic network conditions. Furthermore, the current centralized planning approach will evolve toward decentralized multi-UAV coordination to enhance scalability, resilience, and real-time responsiveness in large-scale deployments.

TABLE II: Performance Comparison of Multi-UAVs Planning Methods

Scenario	Area/APs	UAVs	Method	Avg. Max Path Lengths(m)	QoS (μ/σ)	Total QoS Deficit Time of all UAVs (s) (Avg of 10 Seeds)	Avg. Outage Events of All UAVs	Avg. Total Handover Cases of All UAVs	Avg. Time < QoS Threshold
S1	200x200/4	5	Euclidean Line Distance	139.9	0.8685/0.1676	20.5	7.50	6.6	25.6
			Greedy QoS	209.5	0.87098/0.1988	27.6	8.5	7	31.7
			RSSI-Driven A*	152.9	0.88759/0.1798	18.2	7.8	6.6	24.5
			PQH A*	152.8	0.912/0.1741	15.7	6.8	6	18.9
S2	200x200/4	10	Euclidean Line Distance	132.6	0.5326/0.1574	31.8	11.9	12.6	37.1
			Greedy QoS	171.19	0.5045/0.1717	41.3	17.6	13.8	45.1
			RSSI-Driven A*	133.5	0.5202/0.1641	33.8	13.4	13.4	39.4
			PQH A*	137.3	0.5881/0.1451	29.1	11.2	11.4	30.16
S3	200x200/4	15	Euclidean Line Distance	135.7	0.409/0.1354	53.2	16.9	17.7	61.5
			Greedy QoS	169.3	0.469/0.0972	59.3	21.7	18.3	76.5
			RSSI-Driven A*	145.2	0.390/0.109	46.1	19	17.9	58.5
			PQH A*	148.3	0.519/0.0849	41.1	14.1	16.7	54.5
S4	200x200/4	20	Euclidean Line Distance	128.3	0.319/0.1297	82.3	35.2	22.3	98
			Greedy QoS	181.3	0.369/0.12887	91.1	46.7	24.7	102.3
			RSSI-Driven A*	141.8	0.307/0.1491	78.2	34.2	21.2	87
			PQH A*	141.5	0.411/0.12875	71.8	32.1	20.2	82.4

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