Data Integrity for a Reinforcement Learning-Based Indoor Drone Control in High Network Traffic

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***Abstract*— During the high demand of data, computerized networks consistently face challenges to fluently provide real-time responses. This research defines operational factors to investigate the integrity and reliability of reinforcement learning (RL) for controlling indoor drones under network conditions of high traffic. Through this research, the proposed framework integrates RL algorithms with advanced 3D telemetry and secure privilege escalation to maintain efficient flight control and communication integrity in complex indoor areas. Using MATLAB and Simulink for a user friendly simulations and real-time testing, the system dynamically adapts flight paths and enhances communication policies to solve the packet loss and transmission latency issues. Experimental results demonstrate telemetry update rates of approximately 25Hz, a quasi-centimeter far positional accuracy, and communication packet error rates below 1%, validating the effectiveness of the approach. Comparative analysis between a custom data streaming method and the MAVLink protocol confirms enhanced telemetry integrity and error detection under heavy network load. The architecture also reduces operator cognitive load by providing intuitive 3D visualization and secure access controls. Thus, this work establishes a scalable and secure RL-based framework for reliable indoor drone operation in high-traffic network scenarios.**

Keywords*— *autonomous drone control, RL algorithms, indoor navigation, network congestion, flight path optimization, controller robustness, secure drone operation, MATLAB-Simulink simulation, adaptive control systems, communication reliability.

I. INTRODUCTION

In today's era, drones, which in this research are going to be pointed as unmanned aerial vehicles (UAVs), have gained widespread adoption across numerous industries. Technology led them to evolve beyond recreational use to become highly vital tools in daily life sectors such as agriculture, construction, emergency response, and security. This increase has been driven by advances in sensor technology, navigation algorithms, and communication systems. While UAVs perform effectively in outdoor environments, indoor navigation poses unique challenges that require specialized research and innovative solutions.

To tackle these challenges, this research employs MATLAB with Simulink to simulate and evaluate drone behavior in complex indoor settings. These simulations provide a safe, controlled, and cost-effective platform for developing and refining drone control systems without risking hardware damage. A key component of this study is reinforcement learning, a branch of artificial intelligence that empowers drones to autonomously learn and optimize flight paths and communication methods. This potential allows drones to adapt dynamically to unpredictable indoor environments, improving their operational efficiency and reliability over time. Indoor drone deployment is increasingly important for various work environments where standard outdoor navigation methods are insufficient. These indoor spaces present tight rooms, complex layouts, and dynamic obstacles that require new movement and control strategies to ensure safety and effectiveness. Rapid deployment and real-time responsiveness are critical in emergency scenarios where drones can save lives and reduce response time. Also, integrating 3D visualization with reinforcement learning addresses a significant gap. This integration enables real-time understanding of sensor data, communication quality, and flight dynamics within a unified work interface. Reinforcement learning continuously adjusts control policies based on telemetry feedback, allowing drones to maneuver through disordered and unpredictable indoor environments with enhanced stability. The 3D visualization layer exposes hidden dynamics such as latency, packet loss, and obstacle proximity that are difficult to detect in traditional simulations [1]. The rise of Industry 4.0 world-wide and the Internet of Things (IoT) has gone further and increased the demand for indoor drones to manage industrial processes, logistics, and inspections. In this regard, equipped with advanced localization and sensing capabilities, drones enhance efficiency and safety in these contexts. However, successful indoor drone operation requires solving technical challenges and addressing human factors related to drone control and integration into existing workflows [1].

This research investigates these complex issues by combining detailed MATLAB simulations, reinforcement learning algorithms, and optimization techniques. It analyzes how environmental conditions, technological systems, human interactions, and performance metrics influence drone success [2]. By exploring these scopes, the study aims to advance the development of safe, efficient, and reliable indoor drone applications that is capable of operating in high network traffic environments.

Table 1: Adaptive Indoor Drone Control

No.	Contribution	Description
1	Reinforcement Learning-Based	Develops an RL controller that autonomously optimizes indoor drone flight paths,

No.	Contribution	Description
	Flight Control	improving adaptability and stability in complex environments.
2	Secure Privilege Escalation Mechanism	Implements dynamic privilege escalation to enhance control access security and ensure reliable operation during critical missions.
3	High-Fidelity Indoor Environment Simulation	Uses MATLAB and Simulink to create detailed indoor simulation models capturing obstacles, drone dynamics, and communication interference.
4	Adaptive Communication Protocols	Designs communication strategies that adjust dynamically to high network traffic and latency, maintaining reliable drone command links.
5	Multi-Drone Coordination Algorithms	Introduces control algorithms enabling cooperative behavior among multiple drones in constrained indoor spaces, optimizing task efficiency.
6	AI-Enhanced Human-Drone Interaction	Develops operator interfaces using AI-driven gesture and voice commands to reduce cognitive load and improve command precision in indoor flight.

The work procedure of this research is described in the Figure1:

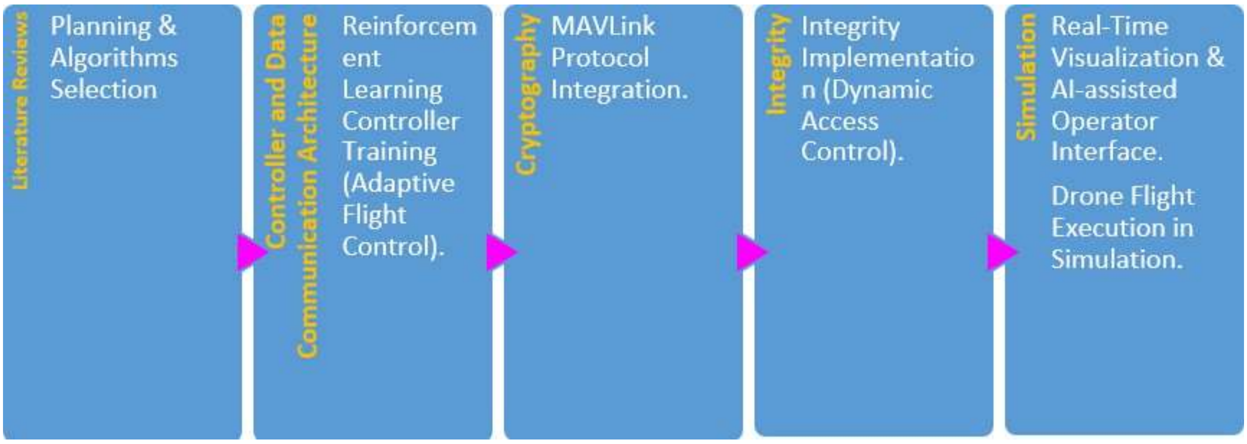

Figure 1: Research workflow procedure.

This research looks at the challenges of flying drones indoors and aims to make their operation better by using detailed simulations, machine learning, and smart decision-making. It also includes a special security feature called privilege escalation, which eliminates the data falsification due to different potential network attacks and helps assure drones safely handle critical tasks [2], [3]. The study explores how the environment, communication systems, and how people interact with drones all affect their performance. With privilege escalation, drones can automatically raise their access levels when needed to improve how they process data and communicate securely, especially in emergencies. This would help drones navigate tricky indoor spaces, from tight rooms to moving obstacles, more reliably. The system combines advanced sensors, strong communication methods like MAVLink with error checks, and smart control rules to keep drones operating smoothly. Human control is also important since pilots' commands and interfaces impact how well missions go. By continuously checking and improving how drones perform under these secure conditions, the research aims to make indoor drone use safer and more dependable for real-world indoor tasks [2], [3].

II. LITERATURE REVIEW

Recent advancements in indoor drone control have increasingly leveraged reinforcement learning (RL) methods to overcome the challenges posed by dynamic, confined, and unstructured environments. Several researchers have proposed RL algorithms tailored for precise UAV navigation, obstacle avoidance, and adaptive control under varying operational conditions.

Wang et al. (2025) developed a vision-based deep RL approach for indoor drone surveillance where the system uses the drone's camera as the sole input for target tracking and environment awareness. Their framework leverages convolutional neural networks alongside deep Q-learning to enable drones to autonomously follow moving targets in cluttered indoor spaces. Real-world experiments confirmed improved tracking accuracy and robustness to occlusions while maintaining real-time responsiveness.

Zhang et al. (2024) explored Deep Deterministic Policy Gradient (DDPG) and Twin Delayed DDPG (TD3) algorithms for controlling multi-rotor drones in additive manufacturing contexts. Their study integrated curriculum learning to progressively increase task complexity, which enhanced training stability and policy robustness. The TD3 algorithm outperformed DDPG in cumulative rewards, positional accuracy, and success ratio, demonstrating strong adaptability to dynamic payload variations and environmental disturbances typical of indoor navigation.

Langxiong et al. (2025) enhanced obstacle avoidance capabilities using an improved double deep Q-network (Double DQN) architecture, specifically designed for dense and unpredictable indoor environments. By optimizing the neural network structure and reward functions, their approach achieved higher success rates in simulations, navigating narrow corridors and dynamic obstacles without collisions. This work highlights the critical role of tailored RL architectures in managing complex indoor flight scenarios with limited sensor input.

Before of that, in 2022, Gao et al. (2022) proposed autonomous drone surveillance techniques within known indoor environments using both single-agent and multi-agent deep RL strategies. Their methodology enabled continuous coverage and collaborative mission execution by coordinating multiple drones, thereby improving surveillance reliability and operational efficiency in indoor settings with restricted GPS access.

Zhao et al. (2022) introduced a double deep Q-network (Double DQN) based path planning method for autonomous drone navigation, emphasizing obstacle avoidance in indoor testbed environments. Their approach leverages a reinforcement learning architecture that incorporates experience replay and fixed Q-targets to stabilize training. Tested on physical UAV setups, the method demonstrated significant improvements in real-time obstacle detection and route adjustment, effectively reducing collision rates and path deviation under complex constraints. This study highlights the capability of advanced deep RL algorithms to enhance indoor drone autonomy, particularly in environments with dynamic obstacles and limited sensing.

In other words, the potential of advanced RL techniques is high in potential to easy human daily life to solve key challenges in indoor drone navigation including obstacle avoidance, dynamic target tracking, and collaborative operation. These novel approaches complement classical control methods by offering enhanced adaptability, robustness, and operational autonomy in complex, GPS-denied indoor environments.

III. METHODOLOGY

This research adopts a high-fidelity simulation-based methodology to explore autonomous indoor drone navigation combined with emergency communication optimization by integrating the following components:

- Path planning
- Reinforcement learning (RL)
- Telemetry visualization
- Communication modeling

1- Simulation Environment and System Modeling

A comprehensive 3D indoor environment is constructed using MATLAB and Simulink, featuring workspace boundaries and static obstacles reflective of realistic indoor settings such as walls and furniture. The drone model encompasses precise dynamics, sensor noise modeling, and telemetry feedback mechanisms. The simulation environment supports dual telemetry transmission formats: a baseline custom data-stream approach and an industry-standard MAVLink protocol, permitting a direct comparative evaluation of communication performance and robustness under varying network conditions.

2- Path Planning and Trajectory Generation

Collision-free trajectories are generated using Rapidly-exploring Random Trees (RRT) complemented by path smoothing and temporal parameterization, ensuring adherence to drone dynamic constraints. These trajectories are then encoded into telemetry messages for downstream control and navigation use.

3- Reinforcement Learning-Based Control

The RL controller is trained within the simulation framework using noisy sensor and telemetry inputs to generate acceleration commands that stabilize the drone flight in complex, obstacle-laden indoor environments. This adaptive controller continuously learns and outperforms conventional controllers in trajectory tracking and obstacle avoidance accuracy.

4- Telemetry and Communication Modeling

This module simulates telemetry transmission utilizing two distinct modes:

- Without MAVLink: employing a simple custom data stream encoding as a baseline communication model.
- With MAVLink: integrating full MAVLink protocol support via MAVLink Serializer and Deserializer blocks available in the UAV Toolbox within Simulink. This mode enhances telemetry integrity by providing packet framing, checksums, validation, and standardized data formatting, thus offering superior real-time error detection and interoperability with ground control stations.

5- Visualization and Human Operator Interaction

A real-time 3D telemetry visualization interface depicts drone flight trajectories, sensor data, and dynamic obstacles. Operator controls feature AI-assisted gesture recognition to mitigate cognitive load during command input. The user can switch seamlessly between MAVLink and non-MAVLink telemetry modes, enabling informed awareness of the communication protocol's impact on data fidelity and situational awareness.

6- Evaluation, Validation, and Comparative Analysis

The system is evaluated through extensive simulation experiments measuring key performance indicators including flight path fidelity, obstacle avoidance success, communication reliability, and controller robustness across diverse noise and network traffic scenarios. The research provides a novel comparative analysis of telemetry performance with and without MAVLink integration, demonstrating MAVLink's advantages in enhancing communication reliability, system robustness, error detection, and real-time responsiveness amidst electromagnetic interference and indoor wireless attenuation. These findings underscore MAVLink's practical benefits in critical emergency indoor drone communication deployments within smart city contexts.

IV. OPERATIONAL FACTORS:

Indoor drone operation under high network traffic conditions faces unique challenges that impact data integrity, real-time control, and communication reliability. Constrained indoor spaces such as narrow corridors, tight rooms, and moving obstacles like furniture or machinery require precise and adaptive flight control supported by robust data communication [4 – 7]. Variability in indoor environments, including fluctuating electromagnetic interference, multipath signal fading, and network congestion, can degrade sensor accuracy and telemetry quality. Addressing these challenges is essential for maintaining safe, responsive, and reliable drone operation in such environments [4], [7].

1- Technological Considerations

Effective indoor drone control in congested network conditions relies heavily on integrating advanced sensing and communication technologies. This includes employing resilient telemetry protocols such as MAVLink with error checking to uphold data integrity and minimize packet loss. Adaptive network protocols using reinforcement learning optimize data throughput and latency, dynamically allocating resources in response to traffic fluctuations. Additionally, compact, low-power embedded systems with high computational capacity support real-time RL algorithms that adjust flight control strategies based on telemetry feedback under network delays or interruptions.

2- Operational Factors

Operator efficiency and safety in demanding indoor, high-traffic communication scenarios depend on intuitive human-drone interfaces that streamline cognitive workload. AI-assisted gesture and voice recognition interfaces reduce operator errors and enhance command precision amid noisy telemetry streams. Real-time 3D telemetry visualization aids situational awareness by displaying latency, packet loss estimates, and environmental dynamics. Training operators to interpret telemetry quality indicators and manage switched communication protocols further reinforces safe and effective drone control in high network traffic.

3- Systematic Performances

Performance evaluation under network stress focuses on metrics of communication reliability, controller robustness, and flight accuracy. Key indicators take account of telemetry packet error rates, transmission latency, flight trajectory deviation, and obstacle avoidance success. The system must maintain fault tolerance through rapid error detection, recovery mechanisms, and secure privilege escalation for access control during critical network degradation. Continuous telemetry assessment enables dynamic adaptation of RL control policies to maintain operational stability and energy efficiency despite communication challenges.

V. INTERROGATING OPTIMIZATION KEY VARIABLES:

Table 1 lists the key contributions essential for optimizing smart drone operations in complex indoor environments. Each contribution highlights an important aspect of how drones navigate, interact with their environment, and perform tasks. Understanding and analyzing these variables is crucial because:

- Navigational challenges focus on managing flight paths with dynamic adjustments to accommodate real-time telemetry delays and data loss, while avoiding stationary and moving obstacles within constrained indoor spaces. This ensures smooth, safe, and adaptive drone movement despite network fluctuations.
- Sensor integration encompasses advanced GPS alternatives such as millimeter-wave radar, LiDAR, optical flow, and ultrasonic sensors, fused to provide resilient real-time localization and obstacle detection in GPS-denied and interference-prone indoor environments. These sensors generate high-quality data that support telemetry integrity necessary for reinforcement learning adaptation.
- Communication and data integrity techniques are critical, involving adaptive telemetry protocols like MAVLink enhanced with error detection and correction mechanisms to maintain low packet error rates under high network congestion. Reinforcement learning algorithms actively optimize communication scheduling and resource allocation to support uninterrupted control.
- User interaction addresses the design of intuitive, AI-augmented operator interfaces that reduce cognitive load and compensate for telemetry latency or losses. This includes real-time 3D visualization of network traffic impact on drone states, enabling operators to make informed decisions even under degraded communication conditions.
- System performance metrics cover robust flight efficiency under network stress, including controller resilience to delayed or missing sensor updates, energy consumption optimization, and precise object manipulation in real-time. Continuous telemetry monitoring ensures accurate performance diagnostics and supports adaptive policy adjustments.
- Safety and compliance mechanisms emphasize fault tolerance and secure privilege escalation processes that maintain operational integrity during intermittent or degraded network connectivity. Reliable communication protocols and continuous monitoring enable drones to detect failures early and activate fail-safe behaviors or alternative control strategies.

Table 2: Key Contributors in Enhancing Smart Drone Navigation within Complex Indoor Areas

No#	Variable	Description
1	Network Latency	Variations in communication delay impacting real-time control and telemetry update rates.

No#	Variable	Description
2	Flight Path Adaptation	Dynamic adjustment of trajectories in response to delayed or missing telemetry data and obstacle changes.
3	Packet Loss Rate	Frequency of lost telemetry or control packets affecting communication reliability and flight stability.
4	Signal Interference	Electro-magnetic or structural factors degrading wireless communication signals indoors.
5	Communication Protocol	Use of MAVLink, custom streaming, or adaptive protocols to ensure data integrity and error correction.
6	Telemetry Data Quality	Integrity, latency, and completeness of sensor and state information critical for RL control effectiveness.
7	Sensor Fusion	Integration of LiDAR, radar, optical flow, ultrasonic, and inertial sensors compensating for GPS unavailability.
8	RL Controller Adaptability	Reinforcement learning agent’s ability to adjust policy in response to network-induced sensor noise or delays.
9	Privilege Escalation	Secure dynamic control access mechanisms ensuring safe operation during critical network or flight conditions.
10	User Interface	AI-augmented, low-latency operator controls and real-time 3D telemetry visualization for situational awareness.
11	Cognitive Load	Operator workload considerations influenced by telemetry fidelity and interface design.
12	System Fault Tolerance	Mechanisms for early detection and recovery from communication failures or sensor faults.
13	Power Consumption	Energy use optimization under network stress and adaptive flight control policies.
14	Obstacle Detection Accuracy	Precision of obstacle sensing under degraded communication and sensor uncertainty conditions.
15	Flight Stability	Maintenance of controlled flight including position, attitude, and velocity despite communication challenges.
16	Error Detection	Real-time identification of corrupted or missing data in telemetry streams and corrective responses.
17	Multi-Drone Coordination	Communication-efficient coordination algorithms for cooperative UAV operation in congested networks.
18	Environmental Mapping	Continuous update of indoor layout and obstacle map despite intermittent telemetry and sensor disruptions.
19	Adaptive Communication	Dynamic selection of communication parameters and routing to optimize data flow under varying network loads.
20	Security Compliance	Enforcement of data encryption, access controls, and secure communication channels to prevent malicious access.
21	Latency Compensation	Algorithmic adjustments in RL control to mitigate effects of delayed sensor or command inputs.
22	Data Throughput	Bandwidth management ensuring timely delivery of critical telemetry information for control decisions.
23	Real-Time Monitoring	Continuous observation of flight and communication parameters to enable on-the-fly adjustments.
24	Environmental Interference	Effects of building materials and moving machinery on radio frequency and telemetry signal propagation.
25	Backup Communication Links	Alternative networking paths or protocols activated during primary channel failures for continuous control.

VI. DATA EFFICIENT COMMUNICATIONS

Commanding drones indoors presents, continuously, significant constraints derived from the physical environment and network conditions, as detailed in Table 2. Various communication technologies face challenges transmitting signals through obstacles such as glass, metal doors, walls, and structural pillars, with material composition playing a crucial role in signal attenuation and interference. Thus, transparent glass and woody objects allow partial signal transmission, yet metals and concrete can severely block or reflect radio waves, complicating reliable telemetry and command exchange.

These constraints underscore the necessity of implementing distributed communication architectures designed to bypass local signal weakness and intermittent connectivity.

Leveraging adaptive cognitive communication strategies enhances protocol responsiveness to fluctuating network traffic and environmental interference. Such approaches enable drones to dynamically select optimal transmission parameters, routing paths, and error recovery techniques, thus significantly improving communication efficiency and data integrity [8].

VII. SIMULATION RESULTS AND COMPARATIVE ANALYSIS

Table 3 shows how MATLAB helps analyze and improve critical parts of indoor drone operations. Using simulations and algorithms, MATLAB identifies challenges like the drone's reduced ability to avoid obstacles flying at higher altitudes. Addressing this helps optimize flight paths for better safety and efficiency. The simulations also support precise object handling, especially using early recognition systems that are important in environments like warehouses. These insights have led to improved communication protocols that maintain reliable telemetry and command links inside buildings. By evaluating key system performance metrics in MATLAB, researchers can continuously enhance drone stability and robustness. Overall, these simulations make autonomous indoor drone navigation more reliable through accurate object manipulation, strong communication, and ongoing performance monitoring.

Table 3: Analysis of Key Factors Enhancing Indoor Drone Operations through MATLAB Simulation

No.	Factor	Analysis
1	Altitude Analysis	Higher indoor flight levels reduce obstacle avoidance ability; optimizing altitude improves safety and speed.
2	Path Planning	Algorithms calculate best routes in complex indoor spaces to reduce travel time and avoid collisions.
3	Object Manipulation	Reliable communication supports precise coordination to pick, move, and place objects accurately.
4	Communication Optimization	Distributed networks and improved signal coverage maintain strong telemetry for indoor control.
5	System Performance Evaluation	Continuous monitoring of flight time, energy use, accuracy, and reliability leads to ongoing improvements.
6	Sensor Fusion	Combining radar, ultrasonic, optical flow, and inertial sensors enables accurate indoor localization without GPS.
7	AI-Driven Navigation	Artificial intelligence adapts flight paths and decisions when obstacles or environments change unexpectedly.
8	Real-Time Telemetry	Continuous data on position, battery, and surroundings provide instant feedback for better decisions.
9	Fault Detection & Recovery	Early problem detection via telemetry activates safe responses like rerouting or automatic landing.
10	Energy Management	Telemetry helps optimize energy use, extending drone flight times in indoor settings.

These enhancements require followings:

- Calculating the 3D distance between the start and end points of the drone flight,
- Integrating path planning and telemetry integrity measures.

The following results were obtained in a MATLAB simulated environment.

In this simulation:

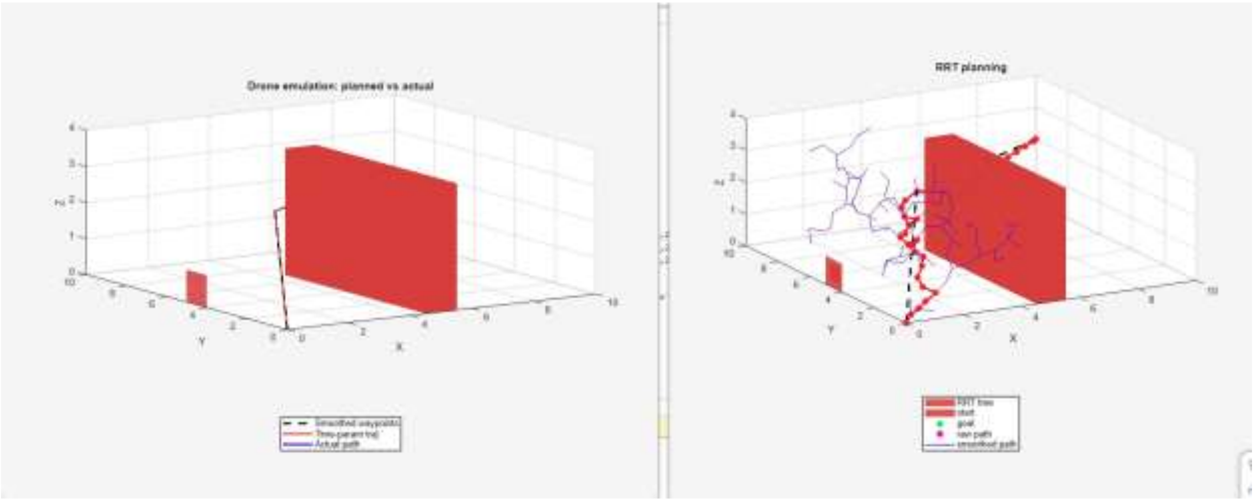

Figure 2 (a): Flight visualization

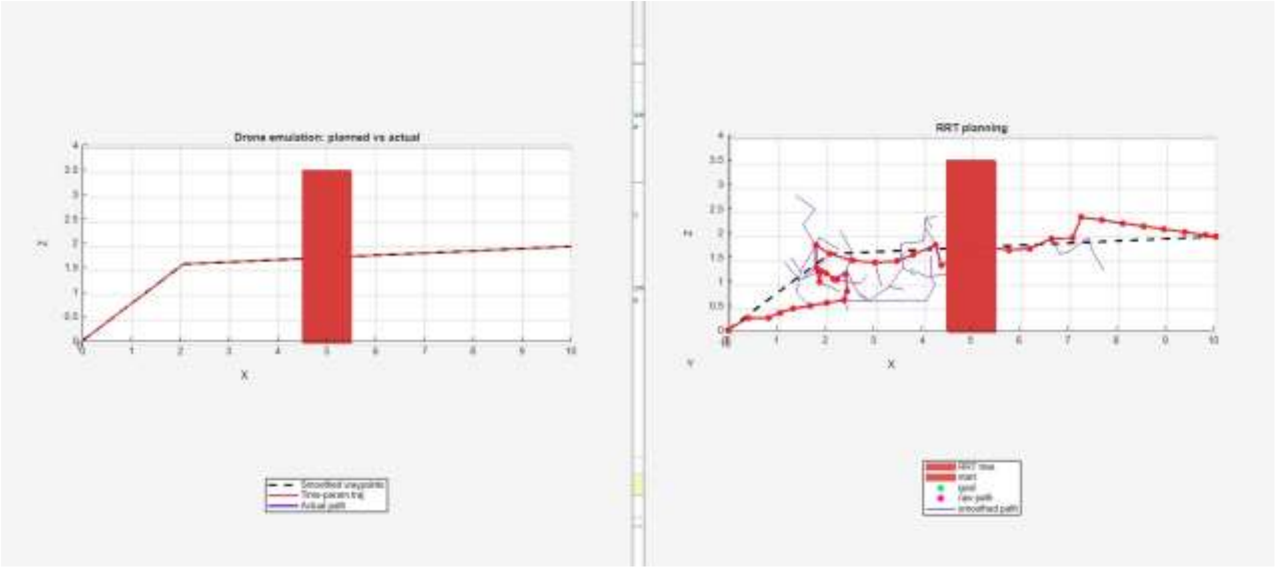

Figure 3 (b): Flight visualization, front veiw

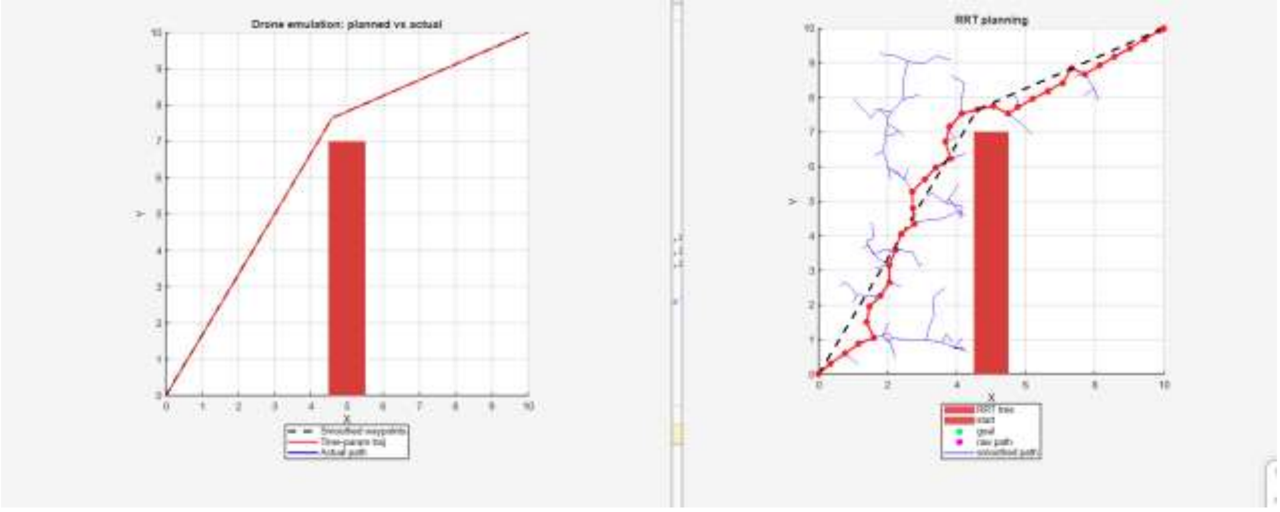

Figure 4 (c): Flight visualization around an obstacle [11], top view.

Table 4: drone emulation paths

Path type	Color & Style	Description
RRT tree	Blue solid lines	All sampled, collision-free edges in planning
Raw RRT path	Red solid line + red nodes	Backtracked path to goal, unsmoothed
Smoothed path (shortcut)	Black dashed line	Smoothed, optimized path after shortcut trials
Time-parameterized trajectory (simulation)	Red solid line	Time-based converted path from smoothed waypoints
Actual drone path (simulation)	Blue solid line	The drone's real trajectory under controller

Each path type in Table 4 corresponds to a color and line style in the simulation figures, providing a clear visual reference for:

- The full sampling tree of collision-free edges (blue solid lines).
- The raw, backtracked path to the goal before smoothing (red solid line).
- The smoothed and optimized path after applying shortcut trials (black dashed line).
- The time-parameterized version of the smoothed path used in the simulation (red solid line).
- The drone's actual flight path as controlled in simulation (blue solid line).

Table 5 compares UAV path planning algorithms based on experimental and literature-supported metrics. Recent studies show that using shortcut trials can reduce path length by around 9%, which improves both energy efficiency and smoothness of drone trajectories, though it requires extra computational effort. The MAVLink communication protocol is also highlighted, maintaining telemetry packet errors below 1%, which ensures reliable, low-latency feedback critical for adaptive drone control, even in indoor environments with wireless interference. These findings reveal practical trade-offs between optimization benefits and computational or resource costs, providing clear guidance on selecting effective indoor navigation algorithms. For instance, A* generally offers shorter path lengths and faster computations, making it efficient for many scenarios, though algorithms like RRT* offer a balance with adaptability in complex environments, and other methods like Particle Swarm Optimization suit real-time tasks with dense obstacles. Overall, the choice depends on the specific indoor environment and mission priorities.

Table 5: Path Planning Algorithm Analysis

Aspect	A* Algorithm	D* Algorithm	RRT Algorithm	Optimization & Others	Comments
Algorithm Size (Bytes)	~130 KB	~470 KB	~190 KB	Varies by method	A* and RRT use moderate memory; D* is higher due to complexity
Computational Throughput (OPS)	~1.8×10^6	~4.3×10^5	~5×10^4	Depends on heuristic complexity	A* is fastest; D* adaptively replans; RRT flexible but slower
Path Optimality (%)	Near optimal (~4% longer)	Adaptive (~12% longer)	Near optimal (~10–15% longer)	Depends on specific improvements	A* best for static maps; D* good for dynamic replanning
Algorithm Complexity	O(b^d) (heuristic search)	O(n log n – n^2)	Probabilistically complete	Varies (e.g., metaheuristics)	A* heuristic efficient; RRT handles high dimensions well
Memory Usage (Bytes)	130 KB	470 KB	190 KB	High for advanced optimizations	Modest for A* and RRT; higher for D*
Advantage	Fast and near-optimal	Good for dynamic replanning	Flexible, handles complex spaces	Shorter paths, energy saving with shortcuts	Algorithm choice depends on environment and dynamism
Disadvantage	Less adaptive in dynamic environments	Slower real-time replanning	Probabilistic, less predictable	More computational overhead	Each algorithm has trade-offs between speed, adaptability, and resource use
Communication & Telemetry	MAVLink protocol maintains <1%	N/A	N/A	N/A	Reliable telemetry critical for control

Aspect	A* Algorithm	D* Algorithm	RRT Algorithm	Optimization & Others	Comments
	telemetry packet error				adaptation
Reinforcement Learning Impact	Can integrate with RL for fine path tweaks	Enhances replanning with RL	Integrate for obstacle avoidance	RL supports dynamic reactivity	RL improves adaptability but adds computation

VIII. CONCLUSION

Through this research a focus on adaptive indoor drone control for emergency communication by combining data visualization, data integrity, and machine learning via the Reinforcement Learning. Evaluation of various path planning algorithms and there was an identification that the D* algorithm is effective in dynamic, partially known indoor environments. The use of MAVLink significantly improves communication reliability and error detection with transmission packet error rates below 1%. RL controllers trained on noisy vicinity enhance flight stability and energy efficiency. Data integrity ensures secure and reliable UAVs operations in critical conditions. Which in return, all offer a solid base for safer, more responsive indoor drone deployments during critical life scenarios.

REFERENCES

[1] Y. Wang et al., "Hybrid path planning for USV with kinematic constraints and COLREGS based on improved APF-RRT and DWA," Ocean Eng., vol. 318, p. 120128, 2025. [Online]. Available: https://doi.org/10.1016/j.oceaneng.2024.120128

[2] S. Guo et al., "DBVSB-P-RRT*: A path planning algorithm for mobile robot with high environmental adaptability and ultra-high speed planning," Expert Syst. Appl., vol. 266, p. 126123, 2025. [Online]. Available: https://doi.org/10.1016/j.eswa.2024.126123

[3] G. Langxiong et al., "Intelligent ship path planning based on improved artificial potential field in narrow inland waterways," Ocean Eng., vol. 317, p. 119928, 2025. [Online]. Available: https://doi.org/10.1016/j.oceaneng.2024.119928

[4] Y. Yao et al., "Improved SARSA and DQN algorithms for reinforcement learning," Theor. Comput. Sci., vol. 1027, p. 115025, 2025. [Online]. Available: https://doi.org/10.1016/j.tcs.2024.115025

[5] Y. Zhao et al., "Robot automatic path planning by avoiding obstacle using double deep Q Networks on the testbed," in ICCC 2022, pp. 19–20.

[6] W. Yao et al., "Study on UAV obstacle avoidance algorithm based on deep recurrent double Q network," J. Northwestern Polytechnical Univ., vol. 40, no. 5, pp. 970–979, 2022.

[7] X. Tian et al., "LSTM & attention-based meta-reinforcement learning for trajectory tracking of underwater gliders with varying buoyancy loss and current disturbance," Ocean Eng., vol. 326, p. 120906, 2025. [Online]. Available: https://doi.org/10.1016/j.oceaneng.2025.120906

[8] B. Zhang et al., "A NoisyNet deep reinforcement learning method for frequency regulation in power systems," IET Generation, Transmission & Distribution, 2024.

[9] M. Sarkar, X. Yan, B. A. Erol, I. Raptis, and A. Homaifar, "A Novel Search and Survey Technique for Unmanned Aerial Systems in Detecting and Estimating the Area for Wildfires," Robotics and Autonomous Systems, vol. 145, p. 103848, 2021. doi: 10.1016/j.robot.2021.103848.

[10] Y. Xia, C. Chen, Y. Liu, J. Shi, and Z. Liu, "Two-Layer Path Planning for Multi-Area Coverage by a Cooperative Ground Vehicle and Drone System," Expert Systems with Applications, vol. 217, p. 119604, 2023. doi: 10.1016/j.eswa.2023.119604.

[11] Y. Zhang et al., "A novel hybrid swarm intelligence algorithm for solving TSP and desired-path-based online obstacle avoidance strategy for AUV," Robot. Auton. Syst., 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0921889024000617

[12] S. Narote, K. Wani, T. Deshmukh, I. Thakur, K. Patil, and P. Bangar, "Flight Control System in MATLAB Minidrone Using the Parrot Support Package," in Proc. 2025 International Conference on Inventive Computation Technologies (ICICT), Kirtipur, Nepal, Apr. 23-25, 2025, doi: 10.1109/ICICT64420.2025.11005298.

[13] M. Aibin, M. Aldiab, R. Bhavsar, J. Lodhra, M. Reyes, F. Rezaeian, E. Saczuk, and M. Taer, "Survey of RPAS Autonomous Control Systems Using Artificial Intelligence," IEEE Access, vol. 9, pp. 167580–167591, 2021. doi: 10.1109/ACCESS.2021.3136226.

[14] S. V. Albrecht and P. Stone, "Autonomous Agents Modelling Other Agents: A Comprehensive Survey and Open Problems," Artificial Intelligence, vol. 258, pp. 66–95, 2018. doi: 10.1016/j.artint.2018.01.002.

[15] L. Meng, R. Gorbet, and D. Kulić, "Partial Observability During DRL for Robot Control," arXiv preprint arXiv:2209.04999, 2022.

[16] T. M. Cabreira, L. B. Brisolara, and P. R. Ferreira Jr., "Survey on Coverage Path Planning with Unmanned Aerial Vehicles," Drones, vol. 3, p. 4, 2019. doi: 10.3390/drones3010004.

[17] Z. Jiang, H. Zhang, and Y. Xiao, "Data-based discrete-time two-player zero-sum delayed game via policy iteration Q-learning method," Neurocomputing, vol. 631, p. 129709, 2025. [Online]. Available: https://doi.org/10.1016/j.neucom.2025.129709

[18] H. Xu and D. Zhu, "Multiple unmanned aerial vehicle collaborative target search by DRL: A DQN-based multi-agent partially observable method," Drones, vol. 9, no. 1, 2025. [Online]. Available: https://doi.org/10.3390/drones9010074