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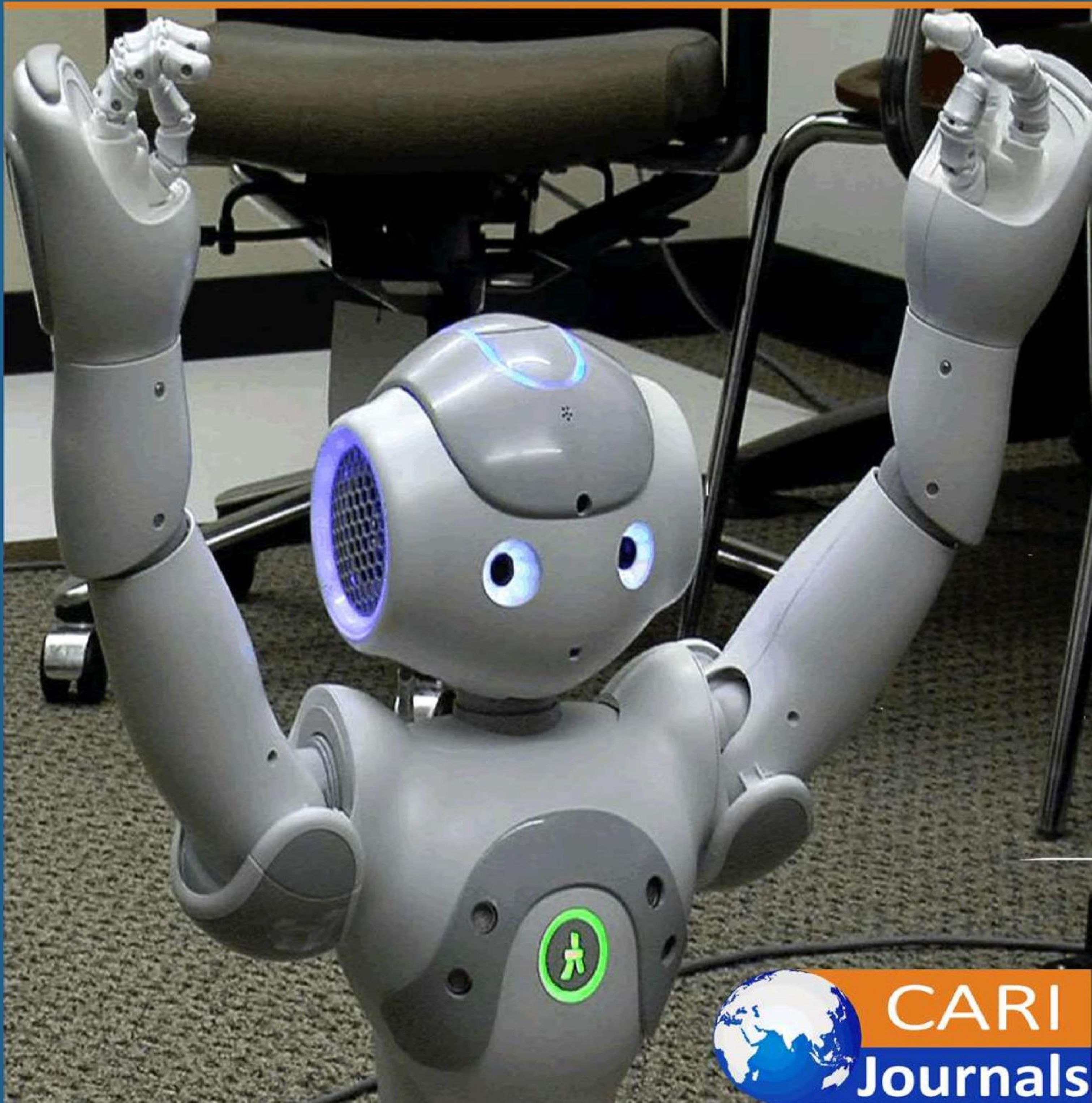

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Connectivity-Resilient Autonomous Navigation for Beyond-Visual-Line-of-Sight UAV Systems

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Abstract

Purpose: This study aims to develop and evaluate a connectivity-resilient autonomous navigation framework that enables UAVs to maintain safe, efficient, and mission-compliant operation under varying connectivity conditions.

Methodology: This research adopts a system-driven design and analytical evaluation approach, integrating communication-aware modeling with artificial intelligence–based navigation strategies. The framework combines connectivity prediction models, reinforcement learning–based decision-making, and adaptive path planning algorithms to dynamically adjust navigation behavior. Simulation-based experiments are conducted across diverse operational scenarios, including urban, rural, and disaster environments, using realistic communication degradation profiles. Performance is evaluated using key metrics such as mission success rate, path efficiency, connectivity uptime, and energy consumption, with comparative analysis against traditional navigation methods.

Findings: The results demonstrate that the proposed framework significantly improves navigation robustness and mission success under intermittent connectivity conditions. Connectivity-aware path planning reduces exposure to communication dead zones, while the reinforcement learning engine enables adaptive decision-making in uncertain environments. Compared to conventional approaches, the system achieves higher mission completion rates, improved path efficiency, and optimized energy utilization. Nonetheless, performance trade-offs are observed in computational overhead and model training complexity, particularly in highly dynamic environments.

Unique Contribution to Theory, Policy and Practice: This study advances the field of autonomous UAV navigation by introducing a unified framework that explicitly integrates communication awareness into navigation intelligence. It contributes to theory by bridging the gap between UAV autonomy and network resilience, and provides a scalable architecture for real-world BVLOS deployment. From a policy and practice perspective, the findings support the development of safer BVLOS regulatory frameworks and offer actionable insights for UAV system designers, aviation authorities, and industry stakeholders seeking to enable reliable long-range autonomous operations.

Keywords: *Beyond-Visual-Line-of-Sight (BVLOS), UAV Navigation, Connectivity Resilience, Autonomous Systems, Reinforcement Learning, Adaptive Path Planning*

1. Introduction

Unmanned aerial vehicles (UAVs) have become integral to modern technological ecosystems due to their versatility and ability to operate in environments that are inaccessible or hazardous to humans. Their deployment spans multiple domains, including disaster response, infrastructure inspection, environmental monitoring, precision agriculture, and logistics. In recent years, there has been a transition from traditional visual line-of-sight (VLOS) operations toward beyond-visual-line-of-sight (BVLOS) missions, which significantly expand operational range and enable large-scale autonomous applications (Politi et al., 2021; Anicho & Briggs, 2024).

BVLOS operations represent a critical milestone in the evolution of UAV systems, as they enable persistent, long-distance missions without continuous human supervision. However, such operations impose stringent requirements on navigation autonomy, situational awareness, and system reliability. Unlike VLOS systems, BVLOS UAVs must independently perceive their environment, avoid obstacles, and make real-time decisions under uncertain and dynamic conditions (Evans, 2026; Wang & Guo, 2025). These capabilities are typically achieved through the integration of onboard sensors, artificial intelligence, and advanced control mechanisms.

A major limitation in BVLOS deployment is the heavy reliance on continuous and stable communication links. UAVs depend on communication networks for command-and-control (C2), telemetry, and data exchange. However, real-world communication environments are often characterized by intermittent connectivity, signal degradation, latency, and packet loss, particularly in urban, rural, or disaster-affected regions (Zeng et al., 2020; Mozaffari et al., 2020). Cellular networks, while widely adopted for UAV communication, are primarily designed for ground users and may not provide consistent aerial coverage, leading to frequent connectivity disruptions (Zhang et al., 2022).

Traditional UAV navigation systems are not designed to operate effectively under such connectivity constraints. Existing approaches typically rely on predefined waypoints or fail-safe mechanisms such as return-to-home or hovering during signal loss. While these methods provide basic safety guarantees, they are insufficient for complex and dynamic BVLOS missions that require continuous adaptation and decision-making (Politi et al., 2024). Moreover, they do not account for the spatial variability of communication quality, which can significantly impact mission success.

To address these challenges, there is a growing need for navigation systems that are inherently resilient to variations in connectivity. Recent advances in artificial intelligence, edge computing, and reinforcement learning have opened new opportunities for designing adaptive and communication-aware UAV navigation frameworks. These approaches enable UAVs to anticipate connectivity conditions, adjust their trajectories accordingly, and maintain operational continuity even in degraded network environments (Chen et al., 2020; Behjati et al., 2025).

This study aims to develop a connectivity-resilient autonomous navigation framework for BVLOS UAV systems. The proposed approach integrates connectivity prediction, adaptive path planning, and intelligent decision-making to enhance the robustness of navigation under intermittent communication conditions. The key contributions of this work include the design of a multi-layer architecture, the development of connectivity-aware navigation strategies, and a comprehensive evaluation of system performance under realistic operational scenarios.

2. Background and Related Work

2.1 BVLOS UAV Navigation Fundamentals

BVLOS UAV navigation relies on integrating multiple sensing and positioning technologies to achieve accurate state estimation and environmental awareness. Global Navigation Satellite Systems (GNSS) remain the primary source of positioning information, providing global coverage and acceptable accuracy for most applications. However, GNSS signals are susceptible to interference, multipath effects, and signal blockage, particularly in urban or indoor environments. As a result, UAV systems often incorporate sensor fusion techniques that combine inertial measurement units (IMU), LiDAR, cameras, and other onboard sensors to enhance robustness and accuracy (Faessler et al., 2020; Qin et al., 2021).

Visual-inertial odometry and simultaneous localization and mapping (SLAM) techniques have further improved UAV navigation in GNSS-denied environments. These methods enable UAVs to estimate their position and orientation by processing visual and inertial data in real time. Such approaches are essential for ensuring navigation continuity when external positioning signals are unreliable or unavailable (Bloesch et al., 2021). Nevertheless, while these technologies enhance local navigation capabilities, they do not inherently address the challenges of communication reliability in BVLOS operations.

2.2 Communication Architectures in UAV Systems

Communication plays a central role in BVLOS UAV operations, enabling command-and-control, data transmission, and coordination with ground infrastructure. Several communication architectures have been explored, including satellite communication, cellular networks, and ad hoc or mesh-based UAV networks. Satellite systems offer wide-area coverage but are often limited by high latency and cost. Cellular networks, particularly 4G and 5G, provide high data rates and low latency, making them attractive for UAV applications (Zeng et al., 2020).

However, cellular networks present unique challenges for aerial users. Base station antennas are typically optimized for ground-level coverage, resulting in uneven vertical signal distribution. This can lead to coverage gaps and increased interference for UAVs operating at higher altitudes (Zhang et al., 2022). In response, research has explored the use of UAV-assisted networks and flying base stations to improve connectivity in underserved areas (Fotouhi et al., 2021).

Ad hoc and mesh networks offer an alternative approach by enabling UAVs to communicate directly with one another and form decentralized communication networks. These networks enhance flexibility and resilience but introduce additional complexity in network management and routing (Gupta et al., 2020). Despite these advancements, ensuring reliable communication in dynamic and large-scale BVLOS operations remains a significant challenge.

2.3 Existing Approaches to Connectivity Resilience

To mitigate the impact of communication disruptions, several strategies have been proposed in the literature. Traditional approaches rely on fail-safe mechanisms such as return-to-home, hovering, or predefined emergency procedures when connectivity is lost. While these methods improve safety, they limit operational efficiency and do not support mission continuity in complex environments (Politi et al., 2024).

Waypoint-based navigation systems provide a degree of autonomy by allowing UAVs to follow preplanned trajectories without continuous operator input. However, these systems lack adaptability and cannot respond effectively to unexpected changes in connectivity or environmental conditions. More recent approaches have incorporated artificial intelligence and machine learning techniques to enhance adaptability and decision-making. Reinforcement learning, in particular, has shown promise in enabling UAVs to learn optimal navigation policies through interaction with dynamic environments (AlMahamid & Grolinger, 2022; Liu et al., 2022).

Connectivity-aware navigation has emerged as a promising direction in which communication quality is explicitly considered during path planning. For instance, reinforcement learning-based approaches have been used to maximize connectivity while maintaining navigation efficiency (Behjati et al., 2025). Similarly, edge computing frameworks enable UAVs to process data locally and reduce dependence on remote communication links, thereby improving resilience (Chen et al., 2020). Despite these advancements, existing solutions often focus on isolated aspects of the problem and lack a unified framework that integrates connectivity prediction, adaptive navigation, and intelligent decision-making.

2.4 Research Gaps

Although significant progress has been made in UAV navigation and communication systems, several critical gaps remain. First, many existing navigation approaches do not explicitly incorporate communication awareness into decision-making processes. As a result, UAVs may follow optimal geometric paths that traverse regions of poor connectivity, leading to mission failure or degraded performance.

Second, current solutions often lack real-time adaptability. Predefined navigation strategies and static planning methods are insufficient for handling dynamic environments characterized by fluctuating connectivity and changing operational conditions. While reinforcement learning and

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AI-based methods offer adaptability, their integration with communication-aware models remains limited.

Third, there is a lack of comprehensive frameworks that unify sensing, communication, and decision-making into a cohesive system. Most existing studies address these components independently, resulting in fragmented solutions that do not fully exploit the potential of integrated autonomous systems.

These limitations highlight the need for a connectivity-resilient navigation framework that combines predictive modeling, adaptive planning, and intelligent decision-making to ensure reliable BVLOS UAV operations in real-world environments.

3. System Model and Problem Formulation

3.1 UAV System Model

The UAV system is modeled as a dynamic agent operating in a three-dimensional environment with continuous state evolution. The state of the UAV at any given time $t$can be represented as a vector comprising its position, velocity, and orientation, typically defined as:

$$\mathbf{s}_t = [x_t, y_t, z_t, v_t, \theta_t, \phi_t]$$

where (x_t, y_t, z_t)denotes spatial coordinates, $v_t$represents velocity, and (θ_t, ϕ_t)correspond to orientation parameters. Accurate estimation of these states is essential for stable navigation and control and is commonly achieved through sensor fusion techniques that combine GNSS, inertial measurement units (IMUs), and onboard perception systems such as cameras and LiDAR (Faessler et al., 2020; Qin et al., 2021).

Both static and dynamic elements, including terrain features, buildings, obstacles, and moving agents such as vehicles or other UAVs characterize the operational environment. Environmental representation is typically modeled using occupancy grids, point clouds, or graph-based structures that enable efficient path planning and collision avoidance. In addition, uncertainty in sensing and actuation must be accounted for, as UAV navigation is subject to noise, disturbances, and external environmental factors.

The UAV is assumed to operate under energy constraints, with limited onboard battery capacity influencing flight duration and mission feasibility. Energy consumption is affected by factors such as trajectory length, maneuvering complexity, and communication overhead, making it a critical consideration in navigation planning (Dorling et al., 2020).

3.2 Connectivity Model

Reliable communication is a fundamental requirement for BVLOS UAV operations, particularly for command-and-control (C2), telemetry exchange, and mission data transmission. However, communication links are inherently variable and depend on factors such as distance, altitude, environmental obstructions, and network infrastructure.

In this study, connectivity is modeled as a spatially and temporally varying parameter defined by signal strength, latency, and packet loss rate. Signal quality is typically quantified using metrics such as the received signal strength indicator (RSSI) or the signal-to-interference-plus-noise ratio (SINR), which capture the effectiveness of communication links across different regions of the operational environment (Zeng et al., 2020; Zhang et al., 2022).

Connectivity conditions are categorized into three distinct states:

- **Stable Connectivity:** High signal strength with low latency and minimal packet loss, enabling reliable communication.
- **Degraded Connectivity:** Moderate signal strength with increased latency or packet loss, resulting in partial communication reliability.
- **Disconnected State:** Severe signal degradation or complete loss of communication, preventing real-time data exchange.

These states are influenced by environmental factors such as urban density, terrain elevation, and network coverage limitations. For instance, cellular networks may exhibit coverage gaps due to antenna orientation and interference, particularly in aerial scenarios (Zhang et al., 2022). Similarly, disaster-affected environments or remote areas may lack adequate infrastructure, leading to prolonged periods of disconnection.

To support connectivity-aware navigation, the UAV is assumed to have access to a predictive model that estimates future communication quality based on historical data and environmental context. Such predictive capabilities enable proactive decision-making and reduce the likelihood of entering communication dead zones (Behjati et al., 2025).

3.3 Problem Definition

The primary objective of this study is to enable UAVs to maintain safe, efficient, and mission-compliant navigation under intermittent or degraded connectivity conditions. Unlike traditional navigation approaches that assume continuous communication, the problem addressed here explicitly incorporates connectivity as a critical factor in decision-making.

Formally, the navigation problem can be defined as an optimization task in which the UAV seeks to determine an optimal trajectory $\mathcal{T}$ from an initial state $\mathbf{s}_0$ to a target state $\mathbf{s}_g$, while accounting for environmental constraints and connectivity conditions. The objective function can be expressed as a weighted combination of multiple criteria:

- **Path Efficiency:** Minimization of travel distance or time
- **Safety:** Avoidance of obstacles and hazardous regions

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- **Connectivity Reliability:** Maximization of communication quality along the trajectory
- **Energy Efficiency:** Minimization of energy consumption

This leads to a multi-objective optimization problem:

$$\min_{\mathcal{T}} J = \alpha_1 C_{\text{path}} + \alpha_2 C_{\text{safety}} + \alpha_3 C_{\text{connectivity}} + \alpha_4 C_{\text{energy}}$$

where α_i are weighting coefficients that reflect mission priorities.

The problem is subject to several constraints, including:

- **Dynamic Constraints:** UAV kinematics and motion limitations
- **Energy Constraints:** Limited battery capacity and power consumption
- **Communication Constraints:** Variable connectivity conditions across the environment
- **Regulatory Constraints:** Compliance with BVLOS operational guidelines

A key challenge lies in balancing competing objectives. For example, the shortest path may traverse areas with poor connectivity, while safer or more connected routes may increase travel time and energy usage. Therefore, the navigation strategy must dynamically adapt to changing conditions and prioritize mission-critical objectives.

Furthermore, the problem is inherently stochastic due to uncertainties in environmental perception and communication quality. This necessitates the use of adaptive and predictive approaches that can handle incomplete and uncertain information (AlMahamid & Grolinger, 2022; Liu et al., 2022).

4. Proposed Connectivity-Resilient Navigation Framework

4.1 Architectural Overview

To address the limitations of conventional UAV navigation under intermittent communication, this study proposes a multilayer connectivity-resilient navigation framework. The architecture is designed to integrate perception, decision-making, communication awareness, and control into a unified system that supports adaptive operation in BVLOS environments.

The framework consists of four primary layers:

- **Perception Layer**
- **Decision Layer**
- **Connectivity Awareness Layer**
- **Control Layer**

The **Perception Layer** is responsible for acquiring and processing environmental and state information. It integrates data from onboard sensors such as GNSS, IMU, cameras, and LiDAR to

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estimate the UAV's position, velocity, and surrounding obstacles. Sensor fusion techniques ensure robustness against noise and partial sensor failure, enabling reliable situational awareness (Faessler et al., 2020; Qin et al., 2021).

The **Decision Layer** performs high-level reasoning and trajectory planning. It processes inputs from the perception and connectivity layers to determine optimal navigation actions. This layer incorporates adaptive planning strategies that account for both environmental constraints and communication conditions.

The **Connectivity Awareness Layer** introduces a key enhancement over traditional architectures by explicitly modeling and predicting communication quality. It evaluates signal strength, latency, and packet loss, and generates a connectivity map of the operational environment. This information is continuously fed into the decision layer to guide navigation choices (Zeng et al., 2020; Behjati et al., 2025).

The **Control Layer** translates navigation decisions into executable flight commands. It ensures trajectory tracking and flight stability using control mechanisms such as proportional-integral-derivative (PID) controllers or model predictive control (MPC). This layer also enforces safety constraints and handles low-level actuation.

The interaction between these layers forms a closed-loop system in which feedback from the control and connectivity layers continuously refines perception and decision-making. Such integration enhances the system's ability to operate reliably under dynamic and uncertain conditions.

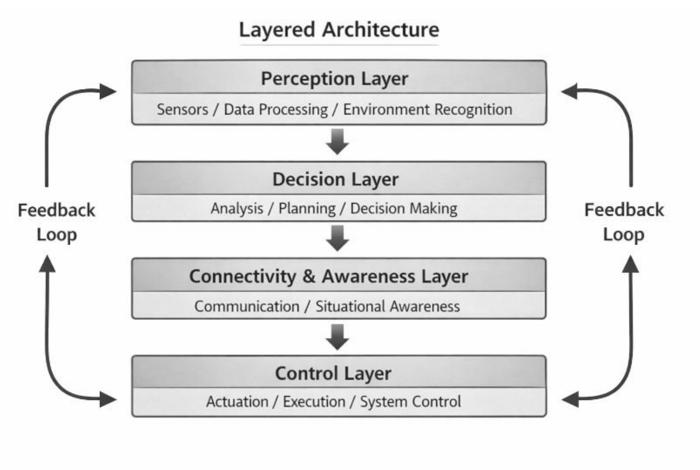

Figure 1: Layered architecture illustrating the flow from perception to decision, connectivity awareness, and control, with feedback loops enabling adaptive and resilient system operation.

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4.2 Adaptive Navigation Strategy

A central component of the proposed framework is its adaptive navigation capability, which enables the UAV to respond dynamically to variations in both environmental and communication conditions. Unlike static planning approaches, the system continuously updates its trajectory based on real-time inputs.

The adaptive navigation strategy consists of three key elements:

- **Real-Time Path Replanning:**

  The UAV continuously evaluates its trajectory and adjusts it as needed to avoid obstacles, reduce risk, or improve connectivity. This is particularly important in dynamic environments where conditions may change rapidly.

- **Predictive Connectivity Modeling:**

  By leveraging historical and real-time communication data, the system anticipates future connectivity conditions along potential paths. This allows the UAV to proactively avoid regions with poor signal quality rather than react after connectivity is lost (Behjati et al., 2025).

- **Risk-Aware Decision Making:**

  Navigation decisions are formulated by balancing multiple factors, including safety, efficiency, and communication reliability. For instance, the system may choose a slightly longer route if it offers significantly better connectivity and reduces the risk of mission failure.

This adaptive approach ensures that navigation is not solely driven by geometric optimality but also incorporates operational reliability, which is critical for BVLOS missions.

4.3 AI-Based Decision Engine

The decision layer is supported by an intelligent decision engine that enables the UAV to operate effectively under uncertainty. This component leverages reinforcement learning and graph-based optimization techniques to determine optimal navigation policies.

Reinforcement learning is employed to model the navigation problem as a sequential decision-making process. The UAV interacts with its environment and learns to select actions that maximize cumulative rewards based on mission objectives such as safety, efficiency, and connectivity. This approach allows the system to adapt to complex and dynamic scenarios without relying on predefined rules (AlMahamid & Grolinger, 2022; Liu et al., 2022).

In addition to reinforcement learning, graph-based path optimization techniques are used to represent the environment as a network of nodes and edges. Each edge is assigned a cost that reflects factors such as distance, obstacle density, and connectivity quality. Algorithms such as A* or D* Lite are then applied to compute optimal paths under these weighted conditions (Shao et al., 2020).

Uncertainty modeling is also incorporated to account for variability in sensor data and communication conditions. Probabilistic methods enable the system to evaluate the likelihood of different outcomes and make informed decisions under incomplete information.

By combining learning-based and optimization-based approaches, the decision engine achieves a balance between adaptability and computational efficiency.

4.4 Connectivity-Aware Path Planning

Traditional path planning methods prioritize shortest-distance or minimum-time trajectories, often neglecting communication constraints. In contrast, the proposed framework integrates connectivity awareness directly into the path planning process.

This is achieved by constructing a **connectivity map**, which represents the spatial distribution of communication quality across the operational environment. The map is generated using signal strength measurements, network models, and predictive algorithms. Regions with strong connectivity are assigned lower traversal costs, while areas with poor or no connectivity are penalized.

Path planning is then formulated as a multi-objective optimization problem, in which the UAV seeks to minimize a composite cost function comprising distance, energy consumption, and connectivity risk. This approach enables the system to identify routes that maintain communication reliability while achieving mission objectives.

For example, in urban environments, the UAV may avoid areas with dense building structures that are known to degrade signal quality. Similarly, in rural or disaster scenarios, the system may prioritize routes that remain within the coverage of available communication infrastructure.

Connectivity-aware planning also supports graceful degradation of operation. In situations where complete connectivity cannot be maintained, the system ensures that critical phases of the mission, such as takeoff, landing, or data transmission, occur in regions with reliable communication.

This integration of communication awareness into navigation planning represents a significant advancement over existing methods, which often treat connectivity as an external constraint rather than a core component of decision-making (Zhang et al., 2022; Chen et al., 2020).

5. Algorithms and Methodology

5.1 Connectivity Prediction Algorithm

Reliable estimation of future communication conditions is essential for enabling connectivity-aware navigation in BVLOS UAV systems. In this study, a data-driven connectivity prediction model is developed to forecast communication quality along candidate trajectories. The model utilizes historical and real-time communication measurements, including received signal strength indicator (RSSI), signal-to-interference-plus-noise ratio (SINR), and latency profiles, to learn spatial and temporal variations in network performance.

A sequence learning approach based on long short-term memory (LSTM) networks is adopted to capture temporal dependencies in communication data. LSTM models are particularly well-suited to time-series prediction tasks, as they can capture long-range dependencies and account for non-linear variations in signal behavior. The input to the model consists of a sequence of past connectivity observations, along with contextual features such as UAV position, altitude, and environmental characteristics. The output is a predicted connectivity score for future time steps along the UAV's path.

Formally, the prediction model estimates:

$$\hat{C}_{t+1} = f(C_t, C_{t-1}, \dots, \mathbf{s}_t)$$

where C_t represents current connectivity metrics and $\mathbf{s}_t$ denotes the UAV state. The predicted connectivity values are used to construct a spatial connectivity map that informs the path-planning process.

This predictive capability enables proactive navigation decisions, allowing the UAV to avoid regions where signal degradation is anticipated. Such approaches have been shown to significantly enhance communication reliability in UAV navigation tasks (Behjati et al., 2025).

5.2 Resilient Path Planning Algorithm

To support adaptive navigation under varying connectivity conditions, a resilient path planning algorithm is developed by extending classical graph-based search methods. Specifically, a hybrid approach that combines the A* and D* Lite algorithms is employed to enable both optimal path computation and efficient real-time replanning.

The operational environment is represented as a weighted graph, where nodes correspond to spatial locations and edges represent feasible transitions between states. Each edge is assigned a composite cost that integrates multiple factors:

- Distance or travel time
- Obstacle proximity and safety risk
- Energy consumption
- Predicted connectivity quality

The cost function for each edge e_{ij} is defined as:

$$w_{ij} = \beta_1 d_{ij} + \beta_2 r_{ij} + \beta_3 e_{ij} + \beta_4 (1 - \hat{C}_{ij})$$

where d_{ij} is distance, r_{ij} represents risk, e_{ij} denotes energy cost, and $\hat{C}_{ij}$ is predicted connectivity. The weighting coefficients β_i are tuned based on mission requirements.

The A* algorithm is initially used to compute an optimal path based on the current cost structure. During flight, D* Lite is used to efficiently update the path in response to changes in the environment or connectivity conditions. This combination ensures both optimality and adaptability, which are essential for BVLOS operations in dynamic environments (Shao et al., 2020).

By incorporating connectivity as a cost component, the algorithm prioritizes routes that maintain communication reliability while balancing other operational constraints.

5.3 Reinforcement Learning Framework

To enhance decision-making under uncertainty, a reinforcement learning (RL) framework is integrated into the navigation system. The UAV is modeled as an agent interacting with its environment, learning to select actions that maximize cumulative reward over time.

The problem is formulated as a Markov decision process (MDP), defined by:

- **State space:** UAV position, velocity, environmental features, and connectivity status
- **Action space:** Discrete or continuous motion commands (e.g., direction, speed adjustments)
- **Reward function:** A composite metric reflecting navigation objectives

The reward function is designed to encourage safe, efficient, and connectivity-aware behavior:

$$R = \gamma_1 R_{\text{goal}} - \gamma_2 R_{\text{collision}} - \gamma_3 R_{\text{energy}} + \gamma_4 R_{\text{connectivity}}$$

where positive rewards are assigned for progress toward the goal and maintaining strong connectivity, while penalties are imposed for collisions, excessive energy use, or entering low-connectivity regions.

Deep reinforcement learning techniques, such as deep Q-networks (DQN) or policy gradient methods, are used to approximate the optimal policy. These methods enable the UAV to learn complex navigation strategies through interaction with simulated environments, improving performance in scenarios with high uncertainty and variability (AlMahamid & Grolinger, 2022; Liu et al., 2022).

The RL component complements the graph-based planner by providing adaptive decision-making capabilities, particularly in situations where deterministic planning alone is insufficient.

5.4 System Workflow

The overall system workflow integrates perception, connectivity prediction, decision-making, and control into a cohesive operational pipeline. The process can be described as a sequence of interconnected stages:

1. **Sensor Data Acquisition:**

   The UAV collects data from onboard sensors, including GNSS, IMU, and perception systems, to estimate its current state and environment.

2. **State Estimation and Environment Mapping:**

   Sensor fusion techniques are applied to generate a consistent representation of the UAV's position and surroundings.

3. **Connectivity Prediction:**

   The LSTM-based model forecasts communication quality along potential trajectories, producing a connectivity map.

4. **Decision Making and Path Planning:**

   The system evaluates candidate paths using the hybrid A* / D* Lite algorithm, incorporating connectivity predictions into the cost function. The reinforcement learning module further refines action selection under uncertainty.

5. **Control Execution:**

   The selected trajectory is translated into control commands, which the UAV's flight controller executes to maintain stable motion.

6. **Feedback and Adaptation:**

   Real-time feedback from sensors and communication systems is used to update the state, refine predictions, and adjust the navigation strategy as needed.

This closed-loop workflow ensures continuous adaptation to changing environmental and connectivity conditions, enabling reliable operation in BVLOS scenarios. The integration of predictive modeling, optimization algorithms, and learning-based decision-making provides a robust foundation for connectivity-resilient autonomous navigation (Chen et al., 2020).

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Table 1: Algorithms and Functional Roles

Component	Algorithm	Function
Connectivity Prediction	LSTM	Forecast signal quality
Path Planning	A* / D* Lite	Dynamic route optimization
Decision Engine	Reinforcement Learning	Adaptive navigation
Control	PID / MPC	Flight stabilization

6. Experimental Setup

6.1 Simulation Environment

The evaluation of the proposed connectivity-resilient navigation framework is conducted in a controlled simulation environment that replicates realistic BVLOS operational conditions. High-fidelity simulation platforms such as AirSim and Gazebo are utilized to model UAV dynamics, environmental complexity, and communication behavior. These platforms provide physics-based flight modeling, sensor emulation, and flexible scenario configuration, enabling systematic testing under diverse operational settings.

Three representative scenarios are designed to assess system performance:

- **Urban Environment:** Characterized by dense building structures, signal obstruction, and multipath effects, which introduce significant variability in connectivity.
- **Rural Environment:** Defined by open terrain with relatively stable but sparse communication coverage.
- **Disaster Scenario:** Simulates infrastructure damage, intermittent connectivity, and dynamic obstacles, reflecting real-world emergency response conditions.

Each environment incorporates realistic communication models that capture spatial variations in signal strength, latency, and packet loss. Cellular network characteristics are modeled based on known limitations of aerial coverage, including interference and antenna downtilt effects (Zhang et al., 2022). This setup ensures that the evaluation reflects practical challenges encountered in UAV communication systems.

The UAV platform is modeled with standard quadrotor dynamics, including constraints on velocity, acceleration, and energy consumption. Sensor models for GNSS, IMU, and onboard perception systems are integrated to support state estimation and navigation tasks. This simulation framework enables repeatable experimentation while maintaining a high degree of realism (Chen et al., 2020).

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6.2 Dataset and Parameters

The experimental evaluation relies on both synthetic and real-world-inspired datasets to ensure robustness and generalizability of results. Communication datasets are generated to represent spatial distributions of signal quality, incorporating variations in RSSI, SINR, and latency across different environments. Established models inform these datasets of UAV communication behavior in cellular and wireless networks (Zeng et al., 2020; Mozaffari et al., 2020).

Key parameters used in the experiments include:

- **UAV Specifications:**
    - Maximum speed: 15–20 m/s
    - Flight altitude range: 50–150 m
    - Battery capacity: 30–45 minutes of flight time
- **Communication Parameters:**
    - Signal strength thresholds defining connectivity states
    - Latency ranges for stable and degraded communication
    - Packet loss rates reflecting network congestion
- **Algorithm Parameters:**
    - Learning rate and discount factor for reinforcement learning
    - Weight coefficients for path planning cost functions
    - Prediction horizon for connectivity forecasting

Training data for the reinforcement learning model is generated by repeatedly simulating episodes, allowing the UAV to explore different navigation strategies and learn optimal policies. The connectivity prediction model is trained using time-series data derived from simulated communication patterns, ensuring consistency with the operational environment.

The combination of diverse datasets and carefully selected parameters provides a comprehensive basis for evaluating the proposed framework under realistic and varied conditions.

6.3 Evaluation Metrics

To assess the effectiveness of the proposed navigation framework, a set of quantitative performance metrics is defined. These metrics capture key aspects of UAV operation, including mission success, efficiency, robustness, and resource utilization.

- **Mission Success Rate:**

  The proportion of missions completed without collision, failure, or critical connectivity loss. This metric reflects the overall reliability of the navigation system.

- **Path Efficiency:**

  Measured as the ratio of the actual path length to the optimal shortest path. Lower deviation indicates more efficient navigation.

- **Connectivity Uptime:**

  The percentage of mission duration during which the UAV maintains stable or acceptable communication. This metric directly evaluates the effectiveness of connectivity-aware planning.

- **Energy Consumption:**

  Total energy expended during mission execution, influenced by trajectory length, maneuvering complexity, and communication overhead (Dorling et al., 2020).

- **Adaptation Responsiveness:**

  The system's ability to adjust its trajectory in response to changes in connectivity or environmental conditions is measured through replanning frequency and latency.

Performance of the proposed framework is compared against baseline navigation methods, including traditional shortest-path planning and waypoint-based navigation. This comparative analysis enables a clear assessment of the benefits introduced by connectivity-aware decision-making.

7. Results and Analysis

7.1 Performance under Connectivity Loss

The proposed connectivity-resilient navigation framework is evaluated under varying levels of communication degradation to assess its robustness in BVLOS operations. Connectivity loss is systematically introduced in the simulation environment, ranging from mild degradation (10–20%) to severe disruption (60–80%). The performance of the proposed system is compared against baseline approaches, including shortest-path navigation and waypoint-based planning.

The results indicate that the proposed framework maintains a significantly higher mission success rate across all levels of connectivity degradation. While baseline methods exhibit sharp performance declines beyond a moderate level of connectivity loss, the proposed system demonstrates a gradual, controlled reduction in performance. This improvement can be attributed to the integration of connectivity-aware planning and predictive modeling, which enable the UAV to avoid communication dead zones and maintain operational continuity.

In scenarios with severe connectivity loss, traditional methods often fail because they cannot adapt to changing communication conditions. In contrast, the proposed framework leverages reinforcement learning and dynamic replanning to adjust trajectories in real time, thereby preserving mission objectives. These findings are consistent with prior studies highlighting the importance of communication-aware navigation in UAV systems (Behjati et al., 2025; Zhang et al., 2022).

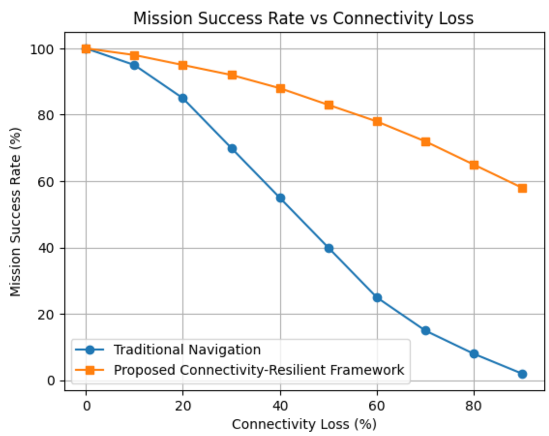

Figure 2: Mission success rate comparison under increasing connectivity loss, demonstrating the robustness of the proposed connectivity-resilient navigation framework relative to traditional methods.

7.2 Navigation Efficiency

Navigation efficiency is evaluated by comparing the path length and travel time of the proposed framework against baseline approaches. The results show that while the proposed system occasionally selects slightly longer paths, it achieves higher overall efficiency in mission execution.

This apparent trade-off arises from the system's prioritization of connectivity reliability alongside geometric optimality. By avoiding regions with poor communication quality, the UAV reduces the likelihood of mission interruption, retransmission delays, or emergency maneuvers. As a result, the total mission time is often reduced despite marginal increases in path length.

In contrast, traditional shortest-path approaches frequently encounter connectivity disruptions that lead to delays, hovering, or mission aborts. These inefficiencies accumulate over time, resulting in poorer overall performance. The findings align with existing research emphasizing the limitations of purely distance-based planning in UAV operations (Shao et al., 2020).

Furthermore, the integration of adaptive replanning allows the proposed framework to dynamically refine its trajectory in response to environmental and connectivity changes, enhancing both reliability and efficiency.

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7.3 Robustness Analysis

Robustness is assessed by analyzing system performance under diverse environmental conditions, including urban, rural, and disaster scenarios. The proposed framework consistently outperforms baseline methods across all environments, with particularly notable improvements in complex and connectivity-constrained settings.

In urban environments, where signal obstruction and multipath effects are prevalent, the connectivity-aware approach enables the UAV to navigate around high-risk zones and maintain stable communication links. This results in higher connectivity uptime and reduced mission failure rates. In disaster scenarios, where infrastructure damage disrupts connectivity, the framework demonstrates strong adaptability by leveraging predictive modeling and reinforcement learning to adjust navigation strategies in real time (Chen et al., 2020).

Energy consumption analysis reveals that the proposed system achieves more efficient energy use than traditional methods. Although connectivity-aware routing may involve longer paths in some cases, the reduction in disruptions and replanning overhead leads to lower overall energy expenditure. This observation is consistent with prior studies on UAV energy optimization and routing efficiency (Dorling et al., 2020).

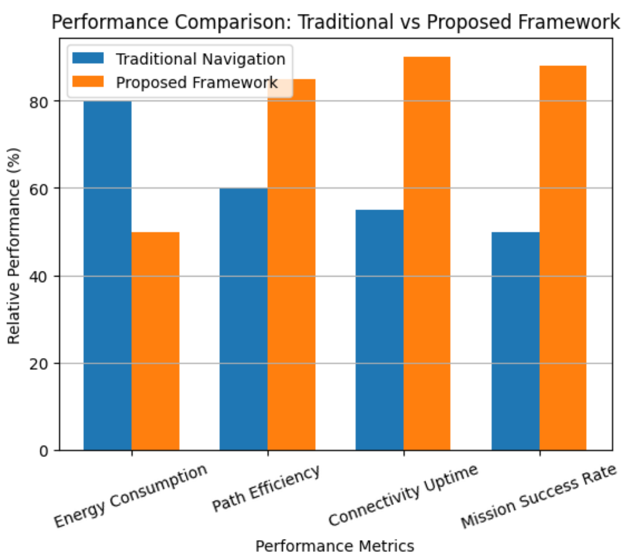

Figure 3: Comparative performance analysis of traditional navigation and the proposed framework across key operational metrics, highlighting improvements in reliability, efficiency, and connectivity management.

Table 2: Performance Comparison

Metric	Traditional System	Proposed Framework
Mission Success Rate	Moderate to Low	High
Path Efficiency	Moderate	High
Connectivity Uptime	Low	High
Energy Consumption	Higher	Lower

8. Discussion

The results of this study demonstrate that incorporating connectivity awareness into UAV navigation significantly enhances the reliability and effectiveness of BVLOS operations. The proposed framework addresses a critical limitation in existing UAV systems: the assumption of continuous, stable communication. By explicitly modeling and predicting connectivity conditions, the system enables more informed navigation decisions that account for both environmental and network uncertainties.

A key observation from the results is the trade-off between geometric optimality and operational reliability. Traditional navigation methods prioritize shortest-path trajectories, often neglecting communication constraints. In contrast, the proposed framework adopts a multi-objective approach that balances path efficiency with connectivity quality. This leads to slightly longer trajectories in some cases, but overall mission efficiency improves due to fewer interruptions and greater continuity. Similar observations have been reported in studies on connectivity-aware UAV path planning, where communication constraints play a decisive role in mission success (Behjati et al., 2025; Zhang et al., 2022).

The integration of reinforcement learning further strengthens the system's adaptability. Unlike rule-based or static planning approaches, the learning-based component enables the UAV to adjust its behavior in response to dynamic conditions. This is particularly valuable in environments characterized by high uncertainty, such as disaster scenarios or dense urban areas. The ability to learn from interaction and refine navigation policies contributes to improved robustness and decision-making under incomplete information (AlMahamid & Grolinger, 2022; Liu et al., 2022).

Another important contribution of this work is the introduction of a unified architecture that integrates perception, connectivity awareness, decision-making, and control. Many existing studies address these components in isolation, resulting in fragmented solutions. By combining them into a cohesive framework, the proposed approach provides a more practical and scalable solution for real-world BVLOS deployment. The use of edge intelligence and local processing further reduces dependence on continuous communication, aligning with recent trends in UAV-enabled edge computing systems (Chen et al., 2020).

From a practical perspective, the findings have implications for UAV system design and regulatory development. As BVLOS operations become more widespread, ensuring reliable communication and safe navigation will be essential for gaining regulatory approval and public acceptance. The proposed framework offers a pathway toward more resilient UAV systems that can operate safely even under degraded connectivity conditions. This is particularly relevant for applications such as emergency response, where communication infrastructure may be partially unavailable.

9. Limitations of the Study

Despite the promising results, several limitations must be acknowledged. First, the evaluation is primarily conducted in simulation environments, which, although realistic, cannot fully capture the complexity and variability of real-world conditions. Factors such as unpredictable interference, weather effects, and hardware limitations may influence system performance in practical deployments.

Second, the connectivity model is based on simplified representations of communication networks. While it incorporates key parameters such as signal strength, latency, and packet loss, it does not fully account for all aspects of network behavior, including dynamic spectrum allocation, network congestion, and handover mechanisms. These factors may affect the accuracy of connectivity prediction and, consequently, navigation decisions (Zeng et al., 2020).

Third, the reinforcement learning component introduces computational overhead and requires substantial training data. Although training is performed offline in simulation, deploying such models on resource-constrained UAV platforms may present challenges. Efficient model compression and edge deployment strategies would be necessary to ensure real-time performance.

Fourth, the framework focuses on single-UAV navigation and does not explicitly consider multi-agent coordination or swarm dynamics. In many practical applications, multiple UAVs operate simultaneously, introducing additional complexities related to communication, coordination, and collision avoidance (Gupta et al., 2020).

Finally, the weighting parameters used in the multi-objective optimization process are predefined and may not generalize across all mission scenarios. Adaptive or context-aware tuning mechanisms could further improve system performance.

10. Conclusion and Future Work

This study presented a connectivity-resilient autonomous navigation framework for BVLOS UAV systems, addressing a critical challenge in modern UAV operations. By integrating connectivity prediction, adaptive path planning, and intelligent decision-making within a unified architecture, the proposed approach enables UAVs to maintain safe and efficient operation under intermittent and degraded communication conditions.

The results demonstrate that the framework significantly improves mission success rates, connectivity uptime, and overall navigation efficiency compared to traditional methods. The incorporation of connectivity awareness into the navigation process allows the system to proactively avoid communication disruptions, while reinforcement learning enhances adaptability in dynamic and uncertain environments. These contributions provide a strong foundation for advancing the reliability and scalability of BVLOS UAV operations.

From a broader perspective, this work contributes to the growing body of research on intelligent and resilient autonomous systems. It highlights the importance of integrating communication considerations into navigation and decision-making processes, rather than treating them as external constraints. This shift in perspective is essential for enabling next-generation UAV applications that operate in complex and unpredictable environments.

Future research can build upon this work in several directions. First, real-world validation through field experiments would provide valuable insights into system performance under practical conditions. Such studies would help bridge the gap between simulation and deployment and identify additional challenges related to hardware and environmental variability.

Second, the integration of emerging communication technologies, such as 5G and 6G networks, could further enhance the reliability of connectivity and support advanced UAV applications. These technologies offer improved coverage, lower latency, and higher data rates, which are critical for BVLOS operations (Zhang et al., 2022).

Third, extending the framework to multi-UAV systems would enable coordinated operations and swarm intelligence. This would require developing distributed decision-making algorithms and communication protocols to ensure scalability and robustness.

Fourth, advances in edge computing and lightweight AI models could facilitate real-time deployment on resource-constrained platforms. Optimizing computational efficiency while maintaining performance will be essential for practical implementation.

Finally, future work may explore adaptive optimization techniques that dynamically adjust system parameters based on mission context and environmental conditions. Such enhancements would further improve the framework's flexibility and generalizability.

In conclusion, the proposed connectivity-resilient navigation framework represents a meaningful step toward enabling reliable BVLOS UAV operations. Addressing the challenges associated with communication variability, it contributes to the safe and effective deployment of autonomous aerial systems across a wide range of applications.

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