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Alpine Swift Routing Protocol (ASRP) for Strategic Adaptive Connectivity Enhancement and Boosted Quality of Service in Drone Ad Hoc Network (DANET)

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Abstract – Drone Ad Hoc Networks (DANETs) are autonomous networks where drones communicate directly to coordinate operations, especially in environments lacking conventional communication infrastructure. These networks face critical challenges related to scalability and routing efficiency, particularly as the number of drones increases. This complexity often leads to higher latency, greater energy consumption, and unstable communication links. The Alpine Swift Routing Protocol (ASRP) has been proposed in this paper to address these issues, inspired by the Alpine Swift bird's agility and efficiency. ASRP dynamically adjusts routing paths based on real-time environmental conditions and network status, enabling the network to maintain optimal performance even as it scales. The protocol initiates with a detailed network scan to assess node positions and signal strengths, followed by continuous adaptations to environmental factors such as wind and node density. Using predictive and reactive algorithms, ASRP ensures stable connections, efficient energy use, and effective data transmission. Simulations conducted in NS-3 to evaluate ASRP's performance demonstrated significant improvements in packet delivery (86.72%), reduced latency (702 ms), lower energy consumption (18.49%), enhanced link stability (9.03 ms), and fewer hops (4.38). These results confirm ASRP's effectiveness in addressing the scalability and routing challenges in large-scale and dynamic DANETs, providing a reliable communication solution in complex scenarios.

Index Terms – Drone Ad Hoc Networks, DANET, Routing, Alpine Swift Routing Protocol, Dynamic Network Adaptation, Energy Optimization.

1. INTRODUCTION

Drone Ad Hoc Networks (DANET) stand at the forefront of technological innovation, enabling drones to form versatile and resilient communication networks autonomously [1]. These networks are characterized by their ability to operate without centralized control, providing high flexibility and scalability. DANETs are particularly useful in scenarios where traditional communication infrastructure is unavailable or impractical, such as remote exploration, disaster management, and military surveillance [2]. The autonomous nature of DANETs allows them to adjust dynamically to the environment and mission objectives, ensuring continuous and reliable communication [3]. Ongoing research and advancements in sensor technology, artificial intelligence, and energy management are crucial to unlocking the full potential of DANETs, paving the way for their widespread adoption and deployment in various critical applications [4].

Innovation in routing strategies for DANET involves continuously refining protocols to address the unique challenges of mobile drone networks. Energy-aware routing

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minimizes energy consumption while maintaining reliable communication links [5]. Techniques such as duty cycling, where drones alternate between active and sleep modes, help conserve battery life and extend the network's operational lifespan. Security is another critical aspect of routing in DANET, with protocols incorporating mechanisms to detect and mitigate potential threats like spoofing, jamming, and data breaches [6]. Enhancing the security features of routing protocols ensures the integrity and confidentiality of transmitted data. Real-time data analytics and sensor technology provide more accurate information on network conditions, enabling more informed routing decisions [7]. Continuous advancement of these strategies promises to make DANET more effective and resilient, capable of supporting a wide range of applications from disaster management to industrial monitoring [8].

Scalability presents a significant challenge in DANETs used for disaster response and recovery, as the number of drones required varies based on disaster scale and complexity. In large-scale disasters, numerous drones may be needed to cover extensive areas, assess damage, locate survivors, and deliver essential supplies [9]. Maintaining efficient and reliable communication routes becomes increasingly complex as the network expands. Constant drone movement leads to frequent changes in network topology, overwhelming existing routing protocols not designed for high dynamism and large node numbers [10]. Environmental factors such as wind further complicate routing, causing drones to change direction and disrupt established communication links. Managing increased network traffic while maintaining low latency, minimizing packet loss, and optimizing energy consumption becomes increasingly challenging [11]. Addressing scalability in DANETs to ensure adequate support for large-scale disaster response operations is crucial for improving community resilience and recovery. Managing large numbers of drones in a constantly changing environment is essential for ensuring comprehensive coverage, timely aid, and effective disaster response. Ensuring scalability in DANETs will enhance their capability to provide robust support in large-scale disaster scenarios [12].

Bio-inspired optimization is essential for advancing communication and routing in drone systems, particularly within complex and ever-changing environments [13]. By drawing inspiration from natural processes and behaviors observed in biological systems, drones can adapt more effectively to challenges such as shifting terrains, obstacles, and dynamic network conditions. This naturalistic approach enables drones to make decentralized decisions, enhancing their ability to coordinate with one another without the need for centralized control [14], [15]. As a result, communication becomes more robust, and routing is optimized for efficiency and reliability. This leads to reduced energy consumption, which is critical for extending the operational lifespan of drones. Bio-inspired strategies contribute to the scalability of drone networks, allowing them to function effectively even as the number of units increases [16]. Incorporating bio-inspired optimization into drone communication and routing systems significantly improves performance, adaptability, and resilience in various applications ranging from environmental monitoring to disaster response.

1.1. Problem Statement

Scalability poses a significant challenge in DANETs due to the network's dynamic and highly mobile nature. As drones increase, maintaining efficient and reliable communication routes becomes increasingly complex. The constant movement of drones leads to frequent changes in network topology, overwhelming existing routing protocols not designed to handle such high levels of dynamism. Environmental factors like wind can further complicate routing by causing drones to change direction and disrupt established communication links. The continuous need to adjust routes and manage increased network traffic can result in higher latency, packet loss, and greater energy consumption. Developing advanced routing protocols that efficiently manage large numbers of highly mobile nodes in a constantly changing environment is essential to address scalability challenges in DANETs.

1.2. Motivation

Scalability presents a significant challenge in DANETs, particularly as the number of drones in the network increases. As the network scales up, route discovery and maintenance complexity escalate, leading to potential increases in latency, overhead, and reduced routing efficiency. More extensive networks require more sophisticated algorithms to manage the increased number of nodes and their dynamic interactions. Ensuring that routing protocols can handle large-scale deployments without performance degradation is critical. Scalable routing algorithms must efficiently manage network resources, support high node densities, and maintain optimal routing paths despite the growing network size. These algorithms should be capable of distributing network load evenly, minimizing routing overhead, and adapting to changes in network topology. Addressing scalability issues is essential for deploying extensive DANETs for large-scale surveillance, environmental monitoring, and disaster response applications. Ensuring robust network performance, regardless of size, will facilitate the effective use of DANETs in various complex and demanding operational scenarios, where maintaining efficient and reliable communication is paramount.

1.3. Objective

This paper aims to design a bio-inspired optimization routing protocol that addresses scalability challenges in DANETs while maintaining routing efficiency. As the number of drones in the network increases, managing route discovery

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and maintenance becomes increasingly complex, potentially leading to performance degradation. The proposed protocol will employ strategies inspired by natural systems to manage increased node interactions and resource allocation efficiently. By optimizing routing paths for large-scale deployments, the protocol aims to ensure robust network performance without compromising scalability. Extensive simulations and real-world applications will validate the protocol's effectiveness in supporting large-scale DANET deployments with high routing efficiency and minimal overhead, ensuring robust network performance regardless of network size.

1.4. Organization

In this paper, Section 1 explains the challenges of DANETs, focusing on issues like scalability, energy consumption, and routing efficiency, elaborating on the difficulties of maintaining efficient communication as drones increase, and highlighting the need for advanced routing protocols to address these challenges. The objective is to develop a bio-inspired routing protocol that dynamically adjusts to network changes while maintaining performance. Section 2 discusses existing routing strategies and their limitations, emphasizing the gap ASRP intends to fill. Section 3 details the methodology, including network scan, environmental adaptation, route discovery, energy management, and error handling. Section 4 presents the simulation results comparing ASRP with AODV and QSCR, demonstrating superior performance in packet delivery, latency, energy consumption, and link stability. Section 5 concludes by summarizing ASRP's effectiveness in addressing the challenges of scalability and routing in large-scale, dynamic drone networks.

2. LITERATURE REVIEW

"Vessel-Drone Routing" [17] integrates vessel and UAV routing for optimized delivery operations using a mixed-integer linear programming (MILP) model. Variables include vessel routes, UAV flight paths, and delivery schedules, aiming to minimize operational costs. A tabu search heuristic iteratively improves solutions by making minor adjustments and avoiding recently visited solutions to explore the solution space. This robust framework addresses joint routing challenges effectively. "Unique and Secure Routing Protocol" [18] ensures reliable and secure data transmission in FANETs through unique routing paths and enhanced security measures. It uses algorithms like A* or Dijkstra's to find optimal routes, considering UAV mobility and network topology. Security is ensured with AES encryption and mutual authentication. The protocol dynamically adjusts to network conditions, enhancing reliability and data integrity, particularly in healthcare applications. "Smart Delivery Synergy" [19] automates last-mile delivery by combining drones with self-driving cars, serving as mobile distribution hubs. Drones handle the final delivery leg, synchronizing with car movements for efficient deliveries. Real-time data optimizes routes for both vehicles and drones. This coordinated approach leverages both technologies to reduce delivery times and enhance logistical efficiency.

"Drone-Enhanced Data Routing" [20] optimizes energy-efficient data routing in landslide-prone areas using WSNs and drones. Drones collect and relay data from sensor nodes, navigating challenging terrains autonomously. Advanced algorithms optimize flight paths and data relay strategies to minimize energy consumption. This integrated approach enhances the reliability and responsiveness of landslide monitoring and early warning systems. "Data Consolidation and Routing" [21] efficiently transmit gathered information to the destination. UAVs collect and aggregate data at intermediate nodes before routing it to the central processing unit. Algorithms like Dijkstra's or A* determine optimal paths, with adaptive techniques dynamically adjusting routes based on real-time conditions. This ensures robust data transmission, minimizing delays and packet loss. "DisastDrone" [22] integrates disaster awareness into a Consumer Internet of Drone Things (IoDT) system within a 6G network. Drones with sensors and communication modules monitor and respond to disaster scenarios in real-time. Drones, leveraging 6 G's high-speed, low-latency capabilities, quickly transmit data to control centres, enhancing situational awareness and the effectiveness of the emergency response.

"Drone Logistics Insight" [11] uses Latent Dirichlet Allocation (LDA) for a systematic review of drone applications in logistics. LDA identifies and categorizes themes in research on drone technology in logistics. This approach provides a structured understanding of current applications and future developments in drone logistics, including last-mile delivery, inventory management, and real-time tracking. "Multi-UAV Last-Mile Optimizer" [23] addresses vehicle routing with multiple UAVs for last-mile logistics using a hybrid distributed optimization approach. Centralized and decentralized techniques coordinate UAVs, dynamically adjusting paths based on real-time data. This iterative process refines routes to achieve optimal delivery efficiency, balancing workload and minimizing travel distance. "Drone Routing Optimization" [24] enhances pickup and delivery operations efficiency with advanced algorithms and optimization techniques tailored to drones' characteristics. Mixed-integer linear programming models optimize routes considering battery life and delivery deadlines. This research is crucial for agile and efficient drone-based delivery systems in various applications. "Bi-Criteria Truck-Drone Routing" [10] coordinates trucks and multiple drones to optimize delivery operations by minimizing delivery time and reducing operational costs. Trucks act as mobile bases, with drones performing last-mile deliveries. The optimization algorithm balances truck routes

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and drone assignments, dynamically adjusting to real-time conditions. This approach enhances logistical performance by leveraging both transportation modes.

"Ad-hoc On-Demand Distance Vector (AODV)" [25] establishes routes by broadcasting RREQ packets and receiving RREP packets from nodes with valid routes. This on-demand mechanism minimizes unnecessary route maintenance, conserving network resources. Under certain conditions, AODV may form routing loops during route discovery, disrupting network operations. Periodic HELLO messages used to maintain neighbor relations contribute to network overhead. Packet delivery delays occur due to route discoveries and potential route failures. Limitations in route caching necessitate frequent route discoveries, increasing overhead. The protocol may perform inadequately in high-speed networks where rapid transmission and processing are essential. Addressing these challenges is crucial to enhancing AODV's efficiency and reliability in various network scenarios. "Q-learning-based Secure and reliable Clustering Routing (QSCR)" [26] involves continuous updates to the learning model and parameters to adapt to changes in drone networks, using a clustering approach for communication management and learning algorithms for optimal route selection. Regular updates are required to keep up with changes in drone behavior and the environment. High mobility in DANETs necessitates frequent route recalculations, increasing computational demands. Delays in cluster formation and maintenance hinder network communication setup. Greedy routing limitations may prevent finding the most efficient paths if the closest cluster head is not ideally positioned toward the destination. Outcomes are sensitive to the discount factor, impacting long-term strategic routing decisions. The summary is listed in Table 1.

Table 1 Comparative Analysis of Scalability Solutions-Oriented Routing Strategies

Name	Methodology	Merits	Demerits	How it Affects Drone Communication
Vessel-Drone Routing [17]	MILP model with tabu search heuristic	Minimizes operational costs, efficient joint routing	Complex implementation, the potential high computational cost	Potential delays due to complex computation and synchronization issues
Unique and Secure Routing Protocol [18]	Dijkstra's algorithm, AES encryption, mutual authentication	Reliable and secure data transmission, adaptable to changing conditions	Potential overhead from encryption and authentication processes	Increased latency and overhead from security protocols
Smart Delivery Synergy [19]	Combining drones with self-driving cars, real-time data synchronization	Reduces delivery times, leverages strengths of both technologies	Dependence on continuous synchronization, complex integration	Risk of communication breakdowns if synchronization fails
Drone-Enhanced Data Routing [20]	WSNs and drones, advanced routing algorithms	Energy-efficient, optimized data transmission, robust landslide monitoring	May require significant initial setup, potential data processing delays	Potential data transmission delays due to initial setup and processing requirements
Data Consolidation and Routing [21]	Data aggregation, Dijkstra's or A* algorithms, adaptive techniques	Robust data transmission minimizes delays and packet loss	Possible overhead from continuous network monitoring and adaptation	Overhead from constant monitoring and real-time route adjustments
DisastDrone [22]	6G network, real-time data transmission, autonomous drones	High-speed, low-latency communication enhances situational awareness	Dependence on advanced network infrastructure, potential high-cost	High dependency on 6G infrastructure, which may not be universally available

Drone Logistics Insight [11]	Latent Dirichlet Allocation (LDA) for topic modelling	Structured understanding of drone applications, identifies trends	May not provide real-time data, relies on existing research corpus	Limited real-time applicability and indirect impact on communication strategies
Multi-UAV Last-Mile Optimizer [23]	Hybrid distributed optimization, real-time data adjustment	Efficient route adjustments, balanced workload	Complex coordination, potential high computational demands	High computational demands can slow down real-time communication and coordination
Drone Routing Optimization [24]	Advanced algorithms, mixed-integer linear programming	Maximizes delivery speed, minimizes costs, improves logistics efficiency	It may require significant computational resources, complex route planning	Computational complexity may lead to delays in real-time communication adjustments
Bi-Criteria Truck-Drone Routing [10]	Mixed-integer linear programming, evolutionary algorithms	Balances delivery time and operational costs, dynamic route adjustment	Complexity in balancing multiple criteria, potential high computational requirements	Complexity can cause delays in route adjustments and communication synchronization

2.1. Technological Gaps

Scalability and routing efficiency in DANET face considerable challenges. Solutions like Vessel-Drone Routing and Unique and Secure Routing Protocols often involve high computational complexity, making them less feasible for real-time applications, integrating security measures such as AES encryption adds latency, degrading performance in dynamic environments. Dependence on advanced algorithms for real-time synchronization and data aggregation in Smart Delivery Synergy and Multi-UAV Last-Mile Optimizer poses significant challenges. Continuous updates and adjustments lead to high computational demands and potential communication delays. Developing scalable, efficient, and secure routing protocols to handle the complexities of dynamic environments while ensuring low latency and high reliability, even with security and real-time data processing burdens, is crucial.

3. ALPINE SWIFT ROUTING PROTOCOL (ASRP)

The Alpine Swift Routing Protocol (ASRP) for DANET is inspired by the agile and efficient behaviors of the Alpine Swift bird. ASRP focuses on optimizing data transmission and network reliability while conserving energy. The protocol involves network scan initialization, environmental adaptation, route discovery, efficient path selection, and dynamic route maintenance.

By employing sophisticated mathematical models and algorithms, ASRP ensures robust error handling, energy management, and adaptive responses to network changes. This approach enhances the drone network's overall performance, resilience, and longevity, making it ideal for dynamic and resource-constrained environments. This section discusses its operation in detail.

3.1. Network Scan Initialization

Network scan initialization resembles the precision of an Alpine Swift scanning its environment, seeking optimal conditions and resources necessary for survival. This analogy deeply intertwines with the initialization phase, where drones meticulously evaluate their environment to establish the groundwork for robust routing pathways.

Mathematically, the drone environment operates laden with variables that significantly influence routing decisions. For instance, consider the representation of all network nodes as N, where each node i in N has attributes such as position, power level, and workload. These attributes can be expressed as vectors in a multidimensional attribute space, as expressed in Eq.(1).

$$a_i = (x_i, y_i, p_i, w_i) \quad (1)$$

where x_i and y_i are the geographical coordinates, p_i the power level, and w_i the workload of node i.

The path loss model governs the relationship between nodes, particularly the signal strength, which dictates the feasibility of establishing a reliable communication link. This model reflects the degradation of signal strength with distance. Eq.(2) is crucial in determining the effective range of communication between drones:

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$$L(d_{ij}) = L_0 + 10_{\gamma} log_{10}(d_{ij}) \quad (2)$$

With $L(d_{ij})$ representing the path loss between nodes i and j, L_0 the loss at a reference distance γ, the path loss exponent, and d_{ij} the distance between the nodes.

To optimize the network scan, drones calculate the potential of each node as a relay based on a function of its attributes and signal strength. The following potential function can mathematically describe this potential as expressed in Eq.(3).

$$P(i) = \frac{1}{w_i + 1} \times \sum_{j \in N} e^{-\alpha L(d_{ij})} \quad (3)$$

where α is a coefficient that moderates the impact of path loss on the relay potential.

The initialization process further entails the assessment of network density, which influences the strategic positioning and deployment of drones. This density is quantified by Eq.(4).

$$D = \frac{1}{|N|} \sum_{i \in N} \sum_{j \in N, j \neq i} \frac{1}{d_{ij}} \quad (4)$$

where D represents the average inverse distance, providing an aggregate measure of node proximity across the network, facilitating decisions on node deployment to enhance coverage and connectivity.

Eq.(5) provides the decision to establish a route from a source node s to a destination node t, which incorporates a comprehensive evaluation of the path costs, integrating energy and reliability considerations.

$$C_{st} = \min_{p \in P} \sum_{(i,j) \in p} (E_{ij} + R_{ij}) \quad (5)$$

where P denotes all possible paths from s to t, E_{ij} the energy cost, and R_{ij} the reliability cost associated with the link from i to j. Initialization of Network Scan is illustrated in Algorithm 1.

Input:

- Set of all nodes N
- Node attributes $a_i = (x_i, y_i, p_i, w_i)$

Output:

- Initial network topology with potential routes identified

Pseudocode:

1. Initialize all nodes in N.
2. For each node i in N:
   - For each node j in N, where $j \neq i$:
   - Calculate the distance d_{ij} using (x_i, y_i) and (x_j, y_j).
   - Calculate the signal strength S_{ij} using d_{ij}.
   - If S_{ij} is greater than the threshold:
   - Add a link (i, j) to the network topology.
3. Return the initial network topology.

Algorithm 1: Initialization of Network Scan

3.2. Environmental Adaptation

Environmental adaption is analogous to the Alpine Swift's efficient use of environmental conditions to aid in its soaring and gliding, which sees drones dynamically adapting their routing strategies based on the real-time assessment of network conditions. The mathematical representation of environmental adaptability begins with characterizing each drone's state by considering multiple parameters influencing operational efficiency. Eq.(6) denotes the state of each drone as a vector s_i consisting of its position, velocity, power reserve, and communication capability:

$$s_i = (x_i, y_i, v_i, p_i, c_i) \quad (6)$$

where x_i, y_i represent the position, v_i the velocity, p_i the power reserve, and c_i the communication capability of drone i.

Environmental factors such as wind speed and direction, electromagnetic interference, and node congestion directly impact routing decisions. These factors can be encapsulated in an ecological impact function $F(e_t)$, which dynamically adjusts based on real-time telemetry data expressed as Eq.(7).

$$F(e_t) = f(w_t, m_t, d_t) \quad (7)$$

where w_i represents wind conditions, m_t is electromagnetic interference, and d_t denotes node density at time t.

To optimize routing decisions, drones compute an adaptability index A_i that factors in the environmental impact and their current state. Eq.(8). helps determine their ability to maintain communication under varying environmental conditions:

$$A_i(t) = \beta . \frac{p_i(t)}{p_{max}} . e^{-kF(e_t)} \quad (8)$$

where β and κ are coefficients that adjust the sensitivity of the adaptability index to power levels and environmental impacts, respectively.

Adjustment in the drone's trajectory and communication strategies is then modeled by a control function $C(s_i, A_i)$.

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Eq.(9) dictates the necessary adjustments to the drone's route and operational parameters to maintain optimal performance:

$$C(s_i, A_i) = g(s_i, A_i).s_{i+1} \tag{9}$$

where g is a transformation function that calculates the next state of the drone based on its current state and adaptability index.

Drones execute a real-time optimization protocol to ensure network resilience and robust data transmission. This is expressed through a network optimization function $O(N, A)$ expressed in Eq.(10), which evaluates all drones' adaptability indices to configure the most stable and efficient routing topology.

$$O(N, A) = min\left(\sum_{i\in N}\sum_{j\in N, i\neq j} L(d_{ij}).(1 - A_i)\right) \tag{10}$$

This function minimizes the total weakened links in the network by adjusting routes and communication strategies based on the collective adaptability of the drones. Environmental Adaptation is shown in algorithm 2.

Input:

- Nodes states $s_i = (x_i, y_i, v_i, p_i, c_i)$
- Environmental impact function $F(e_t)$

Output:

- Adjusted routing strategies

Pseudocode:

1. For each node i in N:
   - Monitor environmental factors e_t.
   - Calculate the environmental impact $F(e_t)$.
   - Update the adaptability index $A_i(t)$.
2. For each link (i, j):
   - Adjust the control function $C(s_i, A_i)$.
3. Return updated routing strategies.

Algorithm 2: Environmental Adaptation

3.3. Route Discovery

Route Discovery mirrors the precision with which Alpine Swifts identify and target their prey. In the context of DANET, this step involves the discovery of viable communication routes through a network-wide scan, effectively seeking paths that promise optimal data transmission with minimal losses. The foundational concept in this step is deploying a probing mechanism where drones broadcast discovery packets across the network. This method is similar to a radar sweep, scanning for potential relay nodes that can facilitate the end-to-end data route. Eq.(11) represents the probability that a link exists between drones i and j at time t.

$$p_{ij}(t) = \sigma\left(r_{ij} - L(d_{ij})\right) \tag{11}$$

where r_{ij} is the received signal strength indicator (RSSI) from drone j to drone i, $L(d_{ij})$ the expected loss over distance d_{ij}, and σ a sigmoid function ensuring p_{ij} ranges between 0 and 1.

The route discovery process is essentially an optimization problem where each drone seeks to maximize its connectivity by selecting links with the highest probabilities. For a given node i, the set of potential next-hop candidates S_i can be determined by Eq.(12).

$$S_i = \{j | p_{ij}(t) > \theta\} \tag{12}$$

with θ being a threshold value dictating the minimum acceptable link probability for inclusion in the route discovery process.

To further refine the route discovery process, the drones calculate the expected effective throughput for each potential link, which measures the data rate that can be realistically achieved given the link conditions. This is modeled as Eq.(13).

$$T_{ij} = B.log_2(1 + SNR_{ij}) \tag{13}$$

where B is the channel bandwidth and SNR_{ij} the signal-to-noise ratio on the link between drones i and j.

A routing table is constructed once each drone has identified its viable links. The table construction uses Dijkstra's algorithm [27] to compute the shortest paths from each drone to all others regarding cost, which is inversely related to the expected throughput as mathematically expressed in Eq.(14).

$$C_{ij} = \frac{1}{T_{ij}} \tag{14}$$

The process of route establishment thus involves each drone iteratively updating its routing table by minimizing the cost C_{ij} as expressed in Eq.(15).

$$R_i = \arg\min_{j\in S_i} C_{ij} \tag{15}$$

This routing table R_i for each drone i then guides the transmission of data packets, aiming to utilize the paths that offer the highest data transfer efficiency. Algorithm 3 defines the route discovery process.

Input:

- Current network topology
- Node attributes

Output:

- Discovered routes with minimal cost

Pseudocode:

1. For each node i in N:
   - Identify neighboring nodes S_i.
   - Calculate the probability $p_{ij}(t)$ for each link (i, j).
   - Calculate the expected throughput T_{ij}.
   - Update the routing table using Dijkstra's algorithm to minimize the cost C_{ij}.
2. Return discovered routes.

Algorithm 3 Route Discovery

3.4. Route Establishment

Route Establishment is crucial for optimizing the network's performance. Following the discovery of potential routes, this step involves evaluating each identified path to establish the most efficient ones based on specific criteria. The primary objective is to minimize energy consumption and maximize reliability, ensuring robust and efficient data transmission. The process begins by assessing the relay potential of each node along the discovered routes. Each discovered route's relay potential is evaluated based on node attributes such as energy levels, processing power, and link quality. This evaluation ensures that only nodes with sufficient resources and stable connections are selected as relays, preventing bottlenecks and ensuring smooth data flow. The routing table is updated to reflect these optimal paths. Paths with the lowest cumulative costs are selected using a modified version of Dijkstra's algorithm. The cost function integrates factors such as energy consumption E_{ij}, reliability R_{ij}, and link quality LQ_{ij}, ensuring a balanced approach to route selection.

This dynamic process ensures the network remains adaptive, continuously updating routes to reflect current conditions. By focusing on energy efficiency and reliability, the ASRP enhances the overall performance and sustainability of the drone network, ensuring that data is transmitted through the most effective and resource-efficient paths. Route Establishment process is depicted in algorithm 4.

Input:

- Discovered routes
- Node attributes

Output:

- Established optimal paths

Pseudocode:

1. For each discovered route:
   - Evaluate the potential of each node as a relay.
   - Establish the most efficient path based on minimum energy consumption and maximum reliability.
2. Return established paths.

Algorithm 4 Route Establishment

3.5. Data Packet Tagging

Data Packet Tagging parallels the precision with which Alpine Swifts select and consume their prey while in motion. For ASRP, this involves the meticulous tagging of data packets based on their priority and type, ensuring that each packet is routed optimally through the network. In this process, each data packet P is assigned a priority level π, which influences its routing path and handling within the network. The priority assignment is based on the packet's content type, source, destination urgency, and other contextual information. This can be modeled mathematically as Eq.(16) and uses a priority function.

$$\pi(P) = \alpha_s . s(P) + \alpha_u . u(P) + \alpha_c . c(P) \tag{16}$$

where $s(P), u(P)$ and $c(P)$ represent the security requirement, urgency, and content value of packet P, respectively. Coefficients α_s, α_u, and α_c are weights that adjust the influence of each factor based on network policies and operational contexts.

Once tagged, the routing of packets is influenced by a combined cost function that considers both the network's current state and the packet's priority. This routing cost for a packet P from drone i to drone j can be described as Eq.(17).

$$C_{ij}(P) = \frac{1}{\pi(P)} . \left(d_{ij} + \lambda . L_{ij}\right) \tag{17}$$

where d_{ij} is the distance between the drones, L_{ij} the current load on the link between i and j, and λ a factor that scales the impact of link load on the routing decision.

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To minimize the total transmission delay and maximize the reliability of high-priority data, drones use Dijkstra's algorithm to update their routing decisions based on the above cost function. The next hop for each packet is selected by Eq.(18).

$$N_i(P) = \underset{j \in S_i}{\operatorname{argmin}}\, C_{ij}(P) \tag{18}$$

where S_i is the set of neighboring nodes to drone i.

A dynamic load balancing mechanism is employed to manage network traffic efficiently and avoid congestion, adjusting the routing paths based on real-time network conditions. This is achieved through an adjustment function expressed in Eq.(19).

$$\Delta_{ij}(P) = \gamma.\left(1 - \frac{L_{ij}}{L_{max}}\right) \tag{19}$$

where γ is a tuning parameter, and L_{max} is the maximum acceptable load on a link. This function reduces the cost C_{ij} for underutilized links, encouraging their use, and preventing congestion on heavily used routes. Data Packet Tagging is illustrated in algorithm 5.

Input:

- Data packets
- Priority levels

Output:

- Tagged data packets

Pseudocode:

1. For each data packet P:
   - Calculate priority $\pi(P)$ based on security, urgency, and content.
2. For each node i:
   - Calculate routing cost $C_{ij}(P)$.
   - Select next-hop $N_i(P)$ using Dijkstra's algorithm.
3. Implement load balancing if necessary.
4. Return tagged data packets.

Algorithm 5 Data Packet Tagging

3.6. Efficient Path Selection

Efficient Path Selection mirrors the Alpine Swift's adept ability to leverage air currents for energy-efficient flight. This step in ASRP focuses on selecting the most energy-efficient paths for data transmission across the network, optimizing the overall energy consumption while maintaining high data transfer reliability and speed. This energy-efficient path selection is crucial because drones, like birds, have limited energy reserves, and they must be managed wisely to maximize their operational lifespan and effectiveness. The decision-making process involves assessing various potential routes based on their energy demands and selecting the optimal balance between energy consumption and transmission efficiency.

The mathematical foundation of Efficient Path Selection starts with quantifying the energy cost associated with transmitting data over different paths. Let E_{ij} represent the energy cost to transmit a packet from drone i to drone j. This cost generally includes the energy required for data processing and the energy expended in overcoming the path loss in communication. Eq.(20) is applied to calculate the total cost of selecting the path.

$$E_{ij} = E_{tx}(i,j) + E_{rx}(j) \tag{20}$$

where $E_{tx}(i,j)$ is the transmission energy, which depends on the distance and required signal strength, and $E_{rx}(j)$ is the reception energy at drone j.

To calculate the transmission energy, Eq.(21) (i.e., Friis transmission strategy) is employed in ASRP, modified to account for drone-specific factors such as antenna characteristics and environmental conditions:

$$E_{tx}(i,j) = P_{tx}.G_{tx}.G_{rx}.\left(\frac{\lambda}{4\pi d_{ij}}\right)^2.\tau \tag{21}$$

where, P_{tx} is the transmission power, G_{tx} and G_{rx} are the transmit and receive antenna gains, respectively, λ is the wavelength of the signal, d_{ij} is the distance between the drones, and τ is the transmission duration.

The optimal route from a source s to a destination t is determined by minimizing the total energy cost over all possible paths. This is done using a modified version of Dijkstra's algorithm, expressed as Eq.(22), incorporating energy cost and a reliability factor to ensure robust data transfer.

$$Cost(p) = \sum_{(i,j)\in p}\left(E_{ij} + \delta.\frac{1}{R_{ij}}\right) \tag{22}$$

where p denotes the path consisting of links $(i,j), R_{ij}$ is the reliability of the link, and δ is the factor that balances energy cost against reliability.

To further enhance energy efficiency, drones can dynamically adjust their transmission power based on the current network conditions and the required quality of service. This adjustment can be modeled as Eq.(23).

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$$P_{tx}^{new} = P_{tx}.\left(1 - \frac{E_{current}}{E_{max}}\right) \quad (23)$$

where $E_{current}$ is the current energy reserve of the drone, and E_{max} is the maximum energy reserve. Efficient Path Selection process is shown in algorithm 6.

Input:

- Current routes
- Energy levels

Output:

- Energy-efficient paths

Pseudocode:

1. For each link (i,j):
   - Calculate energy cost E_{ij}.
   - Adjust transmission power P_{tx}^{new}
2. Optimize path selection to minimize total energy cost.
3. Return energy-efficient paths.

Algorithm 6 Efficient Path Selection

3.7. Agile Response to Network Changes

The agile and responsive flight patterns of the Alpine Swift directly inspire this step. This step involves the capability of the drone network to quickly adapt to sudden changes in the network environment, such as node failures, new node additions, or varying traffic conditions. The agile response mechanism in ASRP utilizes a combination of predictive and reactive strategies to adjust routes dynamically. The foundation of this agility is based on a real-time monitoring system that continuously assesses network status, updating a set of predictive metrics that inform about potential network disruptions before they occur [28].

Each drone in the network continually sends and receives state packets, including information about its state and the network segments it interacts with. ASRP denotes the state information from drone i to drone j as S_{ij}, which includes metrics such as link quality, traffic load, and operational status. Eq.(24) is applied to capture the state information.

$$S_{ij} = \left(LQ_{ij}, TL_{ij}, OS_{ij}\right) \quad (24)$$

where LQ_{ij} is the link quality, TL_{ij} the traffic load and OS_{ij} the operational status (active, idle, error, etc).

Using the result obtained from Eq.(24), each drone calculates a predictive adjustment factor, A_{ij}, which estimates the future state of the link. Eq.(25) is used to adjust routing decisions to avoid potential problems preemptively.

$$A_{ij} = \alpha.exp\left(-\beta.LQ_{ij}\right) + \gamma.TL_{ij} \quad (25)$$

where $\alpha, \beta,$ and γ are weighting factors that balance the importance of link quality and traffic load in the prediction.

A reactive adjustment mechanism is triggered in response to immediate changes or errors detected by the monitoring system. Eq.(26) recalculates routes using a modified cost function that prioritizes stability and quick reconfiguration.

$$R_{ij} = min\left(\frac{1}{LQ_{ij}} + \delta.A_{ij}\right) \quad (26)$$

where δ is a factor that increases the responsiveness to the predictive adjustment factor, ensuring that routes are recalculated to avoid potential disruptions.

Whenever a significant change is detected, the entire route is recalculated using an enhanced version of Dijkstra's algorithm that integrates both the predictive and reactive adjustment metrics, expressed as Eq.(27).

$$New\ Route = \underset{p \in P}{\text{argmin}}\left(\sum_{(i,j)\in p} R_{ij}\right) \quad (27)$$

where P represents all possible paths from the source to the destination.

Dynamic path updates are distributed across the network, ensuring that all drones adjust their routing tables simultaneously to reflect the new optimal paths, mathematically expressed as Eq.(28).

$$UpdatePath_{ij} = if\ \Delta R_{ij} > \varepsilon\ then\ update\ R_{ij} \quad (28)$$

where ΔR_{ij} is the change in the route cost and ϵ a threshold for updating routes. Agile Response to Network Changes is shown in algorithm 7.

Input:

- Current network state
- Predictive metrics

Output:

- Updated routes

Pseudocode:

1. Monitor network state S_{ij}.
2. Calculate the predictive adjustment factor A_{ij}.

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3. Recalculate routes using modified Dijkstra's algorithm.
4. Implement dynamic path updates based on feedback.
5. Return updated routes.

Algorithm 7 Agile Response to Network Changes

3.8. Data Transmission

Data Transmission embodies the seamless and continuous nature of the Alpine Swift's ability to consume food while in flight. This phase focuses on the constant and efficient transmission of data packets across the network. The data transmission process in ASRP is designed to maximize throughput while minimizing delays and packet losses. The underlying mathematical models facilitate the optimization of these parameters, ensuring efficient use of network resources and maintaining high data integrity.

Each link (i,j) in the network has a defined capacity C_{ij}, representing the maximum rate at which data can be transmitted to nodes i and j. The actual data flow F_{ij} is managed to prevent congestion and ensure efficient data distribution, as expressed in Eq.(29).

$$F_{ij} = min(C_{ij}, D_{ij}) \tag{29}$$

where D_{ij} is the demand for data transmission from node i to node j. This formula ensures that the flow does not exceed the link's capacity while attempting to meet the demand as closely as possible.

The network aims to optimize the utilization of its resources to maximize overall throughput. This involves solving a network flow problem using Eq.(30), formulated as a linear programming problem to maximize total flow from a set of sources to a set of sinks.

$$max \sum_{(i,j)\in E} F_{ij} \tag{30}$$

Subject to:

$$\textstyle\sum_{j:(i,j)\in E} F_{ij} - \sum_{j:(i,j)\in E} F_{ji} = 0 \quad \text{for all} \quad i \neq source, sink \tag{31}$$

Eq.(31) ensures the conservation of flow at each node except for the source and sink, indicating that the amount of data entering a node equals the amount of data leaving it, thereby maintaining balance across the network.

The data routing strategy incorporates path latency and error rates to minimize transmission delays and maximize reliability. Each link (i,j) has an associated delay δ_{ij} and error rate ε_{ij}The route selection is adjusted to minimize these factors for high-priority data, expressed in Eq.(32).

$$Cost_{ij} = \lambda_1 \delta_{ij} + \lambda_2 \varepsilon_{ij} \tag{32}$$

where λ_1 and λ_2 are weighting factors that prioritize delay and reliability according to the current network strategy.

Adaptive transmission strategies adjust data rates dynamically based on real-time feedback regarding network conditions. This adaptability is modeled using Eq.(33) by changing the flow rates based on the observed network performance.

$$F_{ij}^{new} = F_{ij}.\left(1 - \alpha.\,\delta_{ij}^{obs}\right) \tag{33}$$

where α is a sensitivity parameter, and δ_{ij}^{obs} is the observed delay on the link (i,j). The process of data transmission is shown in algorithm 8.

Input:

- Established routes
- Network traffic

Output:

- Continuous data flow

Pseudocode:

1. For each link (i,j):
- Calculate link capacity C_{ij} and data flow F_{ij}.
- Optimize network flow to maximize total throughput.
2. Adjust transmission strategies based on feedback.
3. Return continuous data flow.

Algorithm 8 Data Transmission

3.9. Error Handling and Recovery

Error Handling and Recovery reflect Alpine Swift's efficiency in swiftly dealing with its captured prey. Similarly, in ASRP, this step focuses on promptly addressing errors and disruptions in data transmission, ensuring rapid recovery and restoration of the network's functionality. Following the mechanisms of continuous data flow and network optimization discussed in the "Data Transmission" step, this phase involves detecting, correcting, and recovering any errors or packet losses during transmission.

Each data packet transmitted across the network is subject to potential errors and losses, primarily due to unreliable links or environmental interference. The probability of a packet loss on a link (i,j) can be modeled as Eq.(34).

$$P_{loss}(i,j) = 1 - e^{-\lambda.L_{ij}} \tag{34}$$

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where λ is the coefficient reflecting the sensitivity of the link to errors and L_{ij} represents the load or stress on the link, which was dynamically managed in the earlier transmission step.

Upon detecting an error or loss, an immediate recovery mechanism is activated. This involves recalculating the routing paths using a modified version of Dijkstra's algorithm, incorporating an urgency factor for retransmission. Eq.(35) prioritizes links with lower loss probabilities for urgent retransmissions, ensuring quick recovery of lost or corrupted data.

$$R_{ij}^{recovery} = min\left(\frac{1}{1-P_{loss}(i,j)}\right) \quad (35)$$

To enhance reliability, the protocol implements redundancy strategies, including packet replication. This method involves sending duplicate packets over multiple routes, increasing the chances of at least one packet reaching its destination without errors. Eq.(36) is applied to measure the effectiveness of sending duplicate packets.

$$n_{repl} = \left\lceil log_{\left(1-P_{loss}^{min}\right)}\left(1-P_{target}\right)\right\rceil \quad (36)$$

where n_{repl} is the number of replicas needed, P_{loss}^{min} the minimum loss probability among selected routes and P_{target} the target probability of successful transmission.

In addition to redundancy, the adaptive error correction technique utilizes Eq.(37) to adjust the level of error correction coding based on the observed error rates.

$$EC_{level} = \lfloor \beta . \bar{\varepsilon}_{obs} \rfloor \quad (37)$$

where EC_{level} is the level of error correction coding, β a scaling factor, and $\bar{\varepsilon}_{obs}$ the average observed error rate across the network.

A systematic feedback loop continually monitors the outcomes of the recovery processes using Eq.(38) to update the network's error-handling strategies accordingly.

$$Feedback(i,j) = \alpha_f . \left(P_{loss}^{obs}(i,j) - P_{loss}(i,j)\right) \quad (38)$$

where α_f is a feedback sensitivity parameter, and $P_{loss}^{obs}(i,j)$ the observed loss probability after recovery actions. Error Handling and Recovery process is depicted in algorithm 9.

Input:

- Data packets
- Network errors

Output:

- Recovered data and stable network

Pseudocode:

1. Detect errors and calculate packet loss probability $P_{loss}(i,j)$.
2. Activate the recovery mechanism and recalculate routes.
3. Implement redundancy and packet replication strategies.
4. Adjust error correction coding based on observed error rates.
5. Return recovered data and stable network.

Algorithm 9 Error Handling and Recovery

3.10. Dynamic Route Maintenance

Dynamic Route Maintenance captures the essence of the Alpine Swift's behavior of returning to high-altitude flight after feeding about. After addressing errors and recovering from potential disruptions in the "Error Handling and Recovery" step, the network must regularly update and refine its routing paths to adapt to changing environmental and network conditions. This dynamic route maintenance ensures that the network remains agile, reliable, and efficient over time.

Dynamic route maintenance is underpinned by continuous monitoring, where each drone in the network periodically broadcasts its state information, including current position, energy levels, and link quality. The result obtained from Eq.(39) is crucial for maintaining an up-to-date network topology view.

$$S_i = \{x_i, y_i, E_i, LQ_{ij} \forall j \in N_i\} \quad (39)$$

where x_i, y_i are the coordinates, E_i is the energy level and LQ_{ij} is the link quality to each neighboring drone j.

The routing paths are recalculated based on the monitored data to adapt to the dynamic conditions. Route optimization involves recalculating the cost of each potential path while considering the latest network state. The cost function specified in Eq.(40) integrates distance, existing traffic, energy consumption, and link reliability.

$$C_{ij} = \omega_1 . d_{ij} + \omega_2 . T_{ij} + \omega_3 . E_{ij}^{-1} + \omega_4 . LQ_{ij}^{-1} \quad (40)$$

where d_{ij} is the distance, T_{ij} the traffic load, E_{ij} the energy efficiency, LQ_{ij} the link quality, and $\omega_1, \omega_2, \omega_3, \omega_4$ are weighting factors that prioritize these aspects based on current network requirements. The optimization of routes is conducted using a variation of Dijkstra's algorithm that accounts for the multi-faceted cost function, selecting paths

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that minimize the overall cost. Eq.(41) ensures efficient data flow, conserves drone energy, and enhances communication reliability.

$$Optimal\ Route = arg \min_{p \in P} \left(\sum_{(i,j) \in p} C_{ij} \right) \tag{41}$$

where P represents all possible paths from source to destination.

To proactively manage the network, drones adjust their routes based on predictive analytics, forecasting potential network failures or congestions before they occur. It is computed using Eq.(42).

$$\Delta C_{ij} = \gamma . \left(\frac{\partial C_{ij}}{\partial t} \right) \tag{42}$$

where γ is a sensitivity parameter, and $\frac{\partial C_{ij}}{\partial t}$ indicates the rate of change in the cost function over time, allowing for anticipatory adjustments.

Feedback mechanisms are integral to refining the maintenance process. Adjustments are made based on the success rates of previous routing decisions, integrating learning from past actions to continually enhance routing strategies, as specified in Eq.(43).

$$Feedback(i,j) = \eta . \left(C_{ij}^{obs} - C_{ij} \right) \tag{43}$$

where η is a feedback integration factor, and C_{ij}^{obs} is the observed cost of using link i, j after routing decisions. Dynamic route maintenance process is shown in algorithm 10.

Input:

- Current network state
- Node attributes

Output:

- Maintained and optimized routes

Pseudocode:

1. Continuously monitor network state S_i.
2. Recalculate cost C_{ij} for each path.
3. Optimize routes using Dijkstra's algorithm.
4. Proactively adjust routes based on predictive analytics.
5. Return maintained and optimized routes.

Algorithm 10 Dynamic Route Maintenance

3.11. Energy Management

Energy Management reflects the Alpine Swift's remarkable ability to hydrate while soaring at high speeds. This metaphorically parallels the continuous and efficient management of energy resources within the drone network, ensuring that each drone operates optimally without depleting its energy reserves prematurely. After ensuring robust data transmission and optimizing routes in previous steps, this step focuses on strategic energy management across the drone network. The approach involves monitoring, conserving, and efficiently distributing energy among drones to extend operational time and maintain network functionality.

Each drone's energy consumption is tracked with a model that accounts for various operational modes, including idle, transmission, reception, and movement. The energy consumed by drone i during transmission to drone j can be calculated using Eq.(44).

$$E_{ij}^{tx} = P_{tx} . t_{tx} . d_{ij}^{\alpha} \tag{44}$$

where P_{tx} is the power used during transmission, t_{tx} the time spent transmitting, d_{ij} the distance to the receiving drone, and α a constant representing the energy increase with distance.

To optimize energy use, drones dynamically adjust their transmission power based on their remaining energy levels and the required transmission distance, expressed as Eq.(45).

$$P_{tx}^{new} = P_{tx} . \left(\frac{E_i^{current}}{E_i^{max}} \right)^{\beta} \tag{45}$$

where $E_i^{current}$ is the current energy level of drone i, E_i^{max} is its maximum energy capacity, and β is a factor determining the sensitivity of power adjustment to the energy ratio.

An energy redistribution strategy is implemented to balance the energy levels among drones, ensuring that no single drone depletes its energy too quickly. Eq.(46) involves transferring less demanding tasks to drones with higher energy reserves.

$$E_{redist}(i,j) = min\left(E_i^{excess}, E_j^{need} \right) \tag{46}$$

where E_i^{excess} is the excess energy available with drone i, and E_j^{need} is the additional energy required by drone j to perform its tasks effectively.

The routing decisions also incorporate the energy efficiency metric specified in Eq.(47), choosing paths that minimize overall energy consumption without significantly compromising performance.

$$C_{ij}^{energy} = \frac{1}{E_{ij}^{residual}} \tag{47}$$

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where $E_{ij}^{residual}$ is the residual energy after considering the expected energy consumption for a proposed transmission between drones i and j.

A proactive management approach predicts future energy requirements and adjusts operations to prevent crises. This prediction uses Eq.(48) based on past energy usage patterns and anticipated operational demands.

$$E_{future} = E_{current} - \int_{t_0}^{t_1} \dot{E}(t)dt \tag{48}$$

where $\dot{E}(t)$ represents the rate of energy consumption over time from t_0 to t_1. Energy management process is shown in algorithm 11.

Input:

- Energy levels
- Transmission demands

Output:

- Optimized energy usage

Pseudocode:

1. Monitor energy consumption E_{ij}^{tx}.
2. Adjust transmission power P_{tx}^{new} based on energy levels.
3. Implement energy redistribution among nodes.
4. Optimize routing decisions for energy efficiency.
5. Return optimized energy usage.

Algorithm 11 Energy Management

3.12. Termination and Sleep Mode

Termination and Sleep Mode mirrors the Alpine Swift's behavior of resting after long flights to conserve energy. This step focuses on efficiently managing the drones' energy by transitioning them into sleep modes when they are not actively needed, thereby saving battery life and prolonging the operational lifespan of the network. Following the intensive data transmission, dynamic route maintenance, and energy management steps, it is crucial to implement a systematic approach to transition drones into a low-power state when their activity is not required. This approach involves predictive modeling and real-time monitoring to identify optimal times for entering sleep mode.

The state of each drone can be modeled using a finite state machine with states including Active, Idle, and Sleep. The transition probabilities specified in Eq.(49) is between these states depend on current network conditions, energy levels, and task demands.

$$P_{state}(t+1) = \begin{cases} P_{active\rightarrow idle}(t)\ if\ idle\ condition\ met \\ P_{idle\rightarrow sleep}(t)\ if\ sleep\ condition\ met \\ P_{sleep\rightarrow active}(t)\ if\ task\ demand\ arises \end{cases} \tag{49}$$

where $P_{active\rightarrow idle}(t), P_{idle\rightarrow sleep}(t)$, and $P_{sleep\rightarrow active}(t)$ are the probabilities of transitioning between states at time t.

Drones continuously monitor their task queues and energy levels to determine when they can enter an idle state. An idle condition is met when there are no immediate tasks, and the drone's energy level is above a predefined threshold. Eq.(50) is applied for the same.

$$C_{idle} = \left(\sum_{k=1}^{n} T_k\right) = 0 \wedge E_i > E_{min} \tag{50}$$

where T_k represents the tasks in the queue, E_i the current energy level, and E_{min} the minimum required energy to remain operational.

Once idle, the drone evaluates the benefits of entering sleep mode. The sleep mode is activated if the projected idle time exceeds a certain threshold specified in Eq.(51), ensuring that the energy savings justify the transition costs:

$$C_{sleep} = T_{idle} > T_{threshold} \tag{51}$$

where T_{idle} is the projected idle time, and $T_{threshold}$ is the minimum duration that justifies entering sleep mode.

The energy savings from entering sleep mode can be quantified using Eq.(52). It compares the energy consumption in active or idle states with that in sleep mode.

$$E_{savings} = (E_{active} - E_{sleep}).T_{sleep} \tag{52}$$

where E_{active} is the energy consumption rate in the active state, E_{sleep} the energy consumption rate in sleep mode, and T_{sleep} the duration spent in sleep mode.

A wake-up trigger mechanism ensures that drones in sleep mode can be quickly reactivated when needed. This trigger is based on external signals such as network activity, emergency tasks, or scheduled wake-up times. Eq.(53) expresses the wake-up trigger.

$$T_{wake-up} = \begin{cases} Network\ activity\ if\ task\ demand\ arises \\ Scheduled\ time\ \ if\ periodic\ check \end{cases} \tag{53}$$

Combining these models, the overall energy management strategy ensures that drones transition efficiently between active, idle, and sleep states, optimizing energy consumption and extending the network's operational lifespan, as shown in Eq.(54).

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$$min\sum_{i=1}^{n}(E_{active}.T_{active}+E_{idle}.T_{idle}+E_{sleep}.T_{sleep}) \quad (54)$$

where n is the number of drones and $T_{active}, T_{idle,}$ and T_{sleep} are the times spent in each respective state. Termination and sleep model is shown in algorithm 12.

Input:

- Task queues
- Energy levels

Output:

- Drones in sleep mode

Pseudocode:

1. For each drone:
    - Monitor task queue and energy level.
    - If the idle condition is met, transition to the idle state.
    - If sleep condition is met, transition to sleep mode.
2. Calculate energy savings.
3. Implement wake-up triggers.
4. Optimize overall energy management.
5. Return drones to sleep mode.

Algorithm 12 Termination and Sleep Mode

3.13. Framework of ASRP

This section provides an overview of the ASRP's structure and operation. Figure 1 illustrates the flow and framework of ASRP, providing a visual guide to its key processes and interactions within the network. For a deeper understanding, Algorithm 13 presents the pseudocode, detailing the specific steps and logic that underpin the protocol's functionality. This combination of diagrammatic and algorithmic representations ensures a clear and comprehensive understanding of ASRP's operational framework.

Input:

- Set of all nodes N
- Node attributes $a_i = (x_i, y_i, p_i, w_i)$
- Data packets with priority levels

Output:

- Optimized and maintained network with efficient data transmission

Pseudocode:

1. For each node i in N:
    - For each node j in N, where $j \neq i$:
    - Calculate distance d_{ij} and signal strength S_{ij}.
    - If $S_{ij} > threshold$, add a link (i, j) to the topology.
2. For each node i in N:
    - Monitor environmental factors and calculate impact $F(e_t)$.
    - Update adaptability index $A_i(t)$.
3. For each node i in n:
    - Identify neighbors S_i and calculate $p_{ij}(t)$ and T_{ij}.
    - Update the routing table using Dijikstra's algorithm.
4. For each discovered route:
    - Evaluate relay potential and establish efficient paths.
5. For each data packet P:
    - Calculate priority $\pi(P)$ and routing cost $C_{ij}(P)$.
    - Select the next-hop using Dijkstra's algorithm.
6. For each link (i, j):
    - Calculate energy cost E_{ij} and adjust the transmission power P_{tx}^{new}.
    - Optimize paths to minimize energy consumption.
7. Monitor network state and calculate adjustment factors A_{ij}.
    - Recalculate routes and update paths dynamically.
8. For each link (i, j):
    - Calculate C_{ij} and F_{ij}.
    - Optimize network flow and adjust transmission strategies.
9. Detect errors and calculate $P_{loss}(i, j)$.

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- Activate recovery mechanisms and implement redundancy.

10. Monitor network state and recalculate C_{ij}.
    - Optimize routes and adjust proactively.
11. Monitor energy consumption and adjust P_{tx}^{new}.
    - Implement energy consumption and adjust P_{tx}^{new}.
12. For each drone:
    - Monitor task queues and energy levels.
    - If idle conditions are met, transition to an idle state.
    - If sleep conditions are met, transition to sleep mode.
    - Calculate energy savings and implement wake-up triggers.

Algorithm 13 ASRP

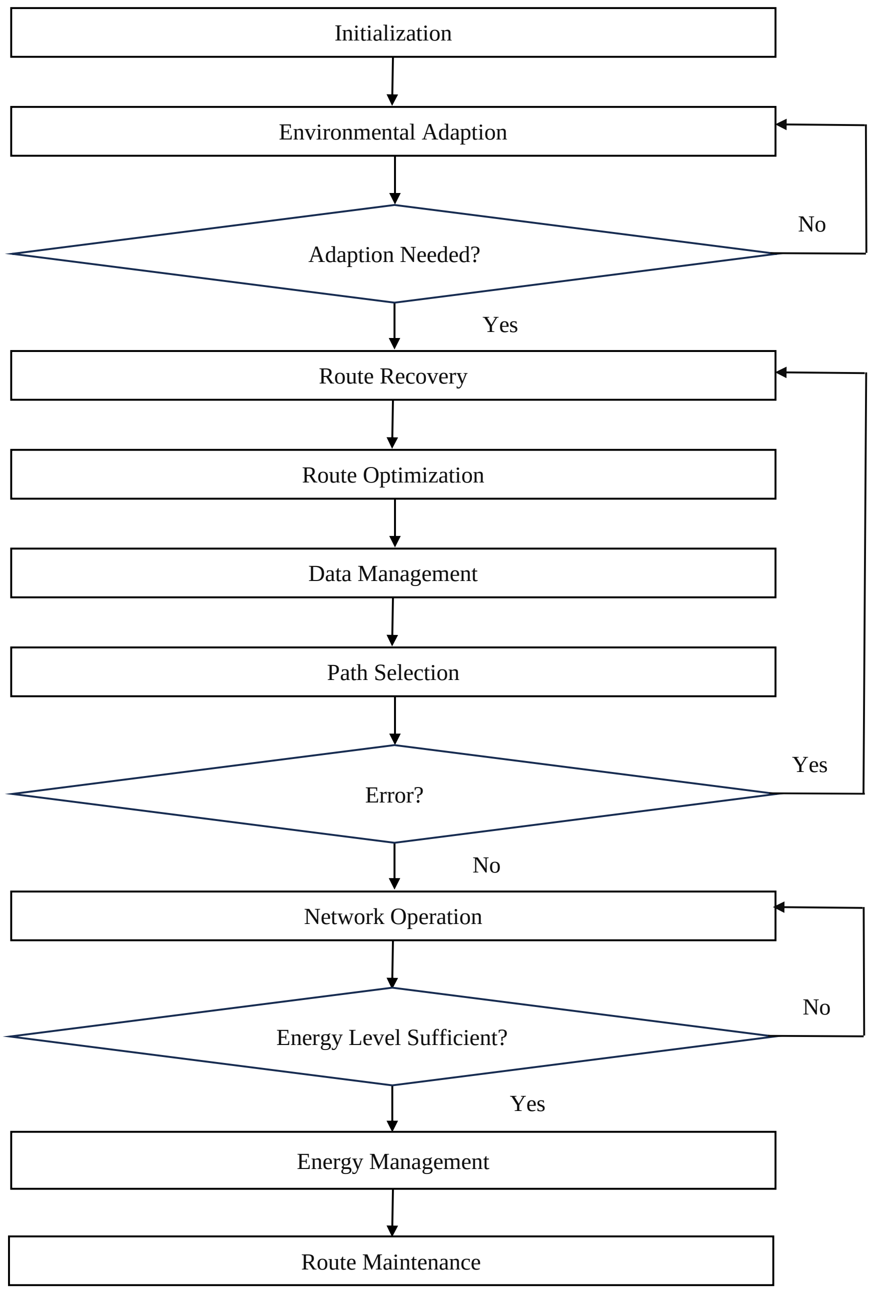

Figure 1 Framework of ASRP

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4. RESULTS AND DISCUSSION

4.1. Simulation Setting

In this research on DANET, the NS-3 simulation tool is used. Simulations run for 900 seconds, with data collected every second and initialized with random seeds. The network features 50 to 500 nodes within a 1000m x 1000m area, employing grid and random topologies and the Random Waypoint mobility model. Communication follows IEEE 802.11 standards. Environmental factors such as wind speed and obstacles are considered. Table 2 provides the simulation settings for evaluating the proposed routing protocol against the state-of-the-art literature.

Table 2 Simulation Setting

Parameter Category	Parameter	Value/Range
General	Simulation Tool	NS-3
	Simulation Duration	900 seconds
	Data Collection Frequency	1 second
	Simulation Seed	Random
Network and Environment Parameters	Nodes	50 - 500
	Environment Dimensions	1000m x 1000m
	Network Topology	Grid, Random
	Model of Mobility	Random Waypoint
	Speed of Drone Movement	5 - 18 m/s
	Standby Time	20 - 180 seconds
	Environmental Factors	Wind Speed, Obstacles
Communication Parameters	MAC and PHY Layers	IEEE 802.11
	Transmission Range	80m - 240m
	Channel Bandwidth	20 MHz
	Interference Model	Basic, Detailed
	Propagation Model	Two-Ray Ground Reflection
	Path Loss Model	Free Space, Two-Ray Ground
	Collision Avoidance Mechanism	RTS/CTS
Traffic and Protocol Parameters	Protocol	AODV, DSR, OLSR, etc.
	Traffic Pattern	CBR (Constant Bit Rate)
	Packet Size	256 bytes
	Transmission Rate	2 Mbps - 12 Mbps
	Packet Interval	0.2 - 1 second
	Queue	FIFO, DropTail
	Control Packet Interval	0.5 - 5 seconds
	Congestion Control Mechanism	TCP, UDP
Energy Parameters	Initial Energy	1000 Joules
	Energy Model	Linear Battery Model
	Sleep Mode Energy Consumption	0.1 Joules/second
	Packet Transmission Energy	0.5 Joules/packet
	Packet Reception Energy	0.3 Joules/packet

4.2. Packet Delivery Ratio and Packet Loss Ratio Analysis

Figure 2, titled “Packet Delivery Ratio and Packet Loss Ratio Results,” showcases the number of drones on the X-axis, ranging from 50 to 500. The left side of the Y-axis represents the Packet Delivery Ratio (PDR), and the right side displays the Packet Loss Ratio (PLR), with both metrics measured in percentages. These values are crucial for assessing the effectiveness and reliability of network communications. The PDR, represented on the left side of the Y-axis, quantifies the percentage of packets that successfully reach their intended destination, serving as a gauge of network reliability. The PLR, detailed on the right side of the Y-axis, calculates the percentage of packets that do not reach their destination, indicating potential inefficiencies or problems within the network’s routing protocols. Degradation in AODV’s performance, reflected in the data from Table 3, arises from its susceptibility to loop formations during route discovery. This issue leads to unnecessary routing loops, significantly increasing packet loss and decreasing delivery rates, particularly as the network expands in drone numbers. QSCR’s performance is negatively impacted by its dependency on dynamic cluster formations. The constant adjustments required in the high-mobility environment of DANETs lead to delays and disrupt routing accuracy, adversely affecting the Packet Delivery and Loss Ratios.

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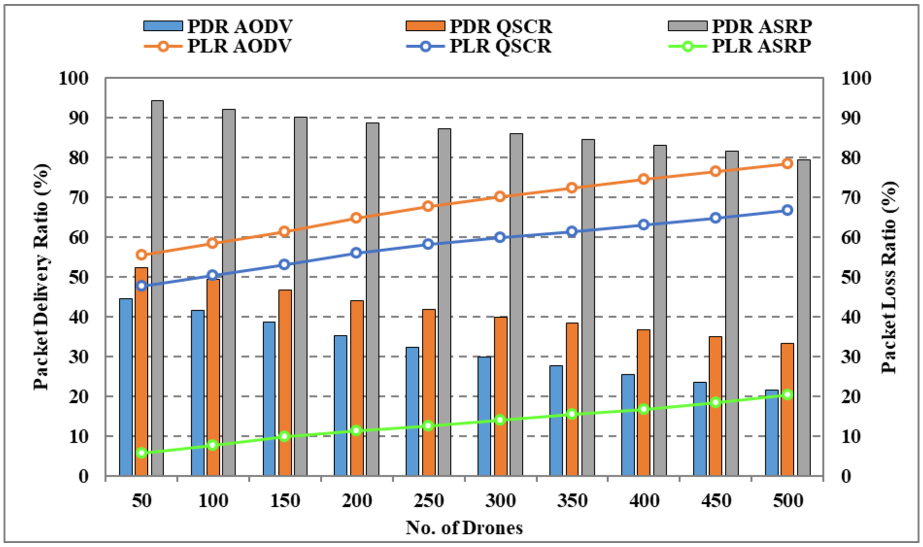

Figure 2 Packet Delivery Ratio and Packet Loss Ratio Results

Table 3 Packet Delivery Ratio and Packet Loss Ratio Result Values

	Packet Delivery Ratio (%)			Packet Loss Ratio (%)		
No. of Drones	AODV	QSCR	ASRP	AODV	QSCR	ASRP
50	44.492	52.260	94.290	55.508	47.740	5.710
100	41.557	49.538	92.208	58.443	50.462	7.792
150	38.696	46.866	90.119	61.304	53.134	9.881
200	35.178	44.049	88.639	64.822	55.951	11.361
250	32.268	41.841	87.269	67.732	58.159	12.731
300	29.881	40.044	85.967	70.119	59.956	14.033
350	27.680	38.501	84.537	72.320	61.499	15.463
400	25.530	36.788	83.126	74.470	63.212	16.874
450	23.549	35.088	81.544	76.451	64.912	18.456
500	21.541	33.251	79.557	78.459	66.749	20.443
Average	32.037	41.823	86.726	67.963	58.177	13.274

ASRP demonstrates significant performance improvements across various drone densities. Its design effectively manages node mobility and adapts to substantial changes in network topology without declining performance. The robustness of ASRP in adverse conditions and its compatibility with various network architectures improve its packet-handling capabilities. This is evidenced by consistently lower packet loss and higher delivery rates compared to AODV and QSCR, as shown in Table 3. ASRP's ability to maintain high efficiency and reliability suits it, particularly for complex and dynamic networks like DANETs.

4.3. Latency Analysis

Figure 3, titled "Latency Analysis Results," presents how latency, measured in milliseconds, scales with the number of drones from 50 to 500. This data highlights how each routing

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protocol handles the increasing demands of larger network configurations.

In the analysis of latency based on Table 4, AODV shows an upward trend in latency as the network size increases, with an average latency of 3907 milliseconds. This increasing delay is primarily due to AODV's reliance on periodic HELLO messages needed to maintain network topology. While these messages are crucial for connectivity, they also add significant overhead, slowing the network as more drones participate. QSCR, designed to handle dynamic clustering, also exhibits increasing latency, averaging 3312 milliseconds. The protocol's need to frequently update and recalculate routes in response to drone mobility introduces additional delays. Each recalculation, necessary to maintain accurate cluster information, adds to the time it takes for packets to navigate the network, thus extending latency significantly as the number of drones increases.

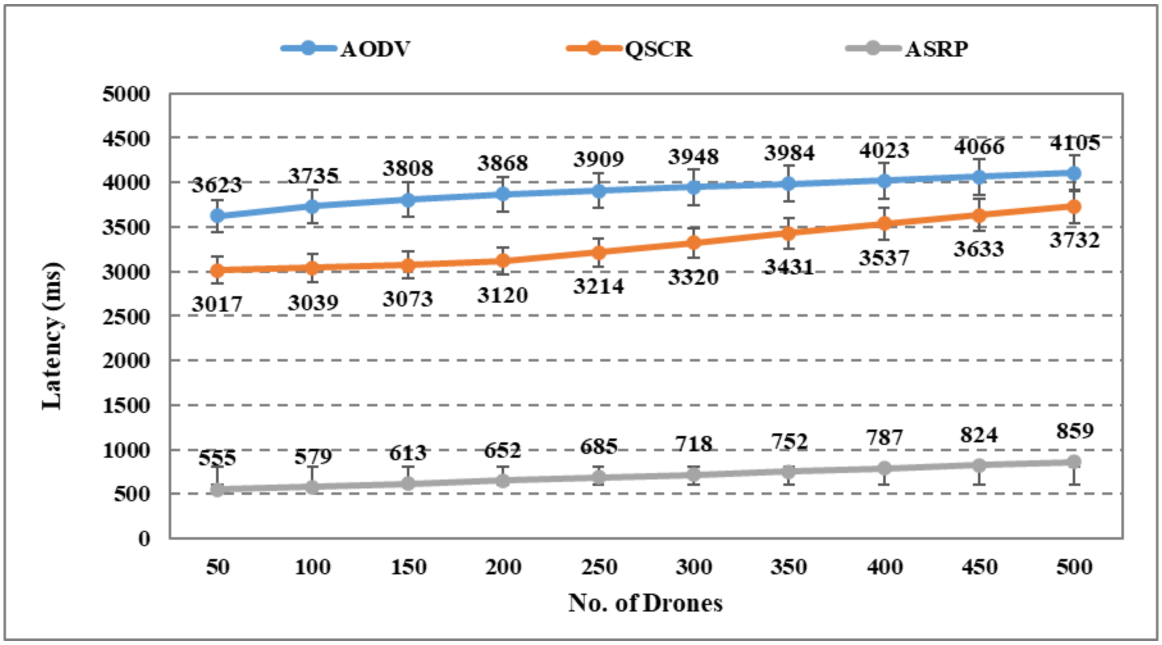

Figure 3 Latency Analysis Results

Table 4 Latency Analysis Result Values

No. of Drones	AODV (ms)	QSCR (ms)	ASRP (ms)
50	3623	3017	555
100	3735	3039	579
150	3808	3073	613
200	3868	3120	652
250	3909	3214	685
300	3948	3320	718
350	3984	3431	752
400	4023	3537	787
450	4066	3633	824
500	4105	3732	859
Average	3907	3312	702

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ASRP stands out with its markedly lower average latency of 702 milliseconds across varying drone counts. This efficiency is attributed to ASRP's design, which adapts swiftly to changes in network topology without excessive recalculations or routing overhead. By minimizing the time packets remain in transit and reducing the need for frequent network-wide updates, ASRP ensures faster packet delivery and significantly lowers latency, proving its effectiveness in managing dynamic and complex drone networks.

4.4. Energy Consumption Analysis

Figure 4, "Energy Consumption Results," quantifies the energy consumption rates for different routing protocols as a function of increasing drone counts, ranging from 50 to 500. This figure, supported by data from Table 5, highlights the direct impact of routing efficiencies on energy utilization across varied network scales.

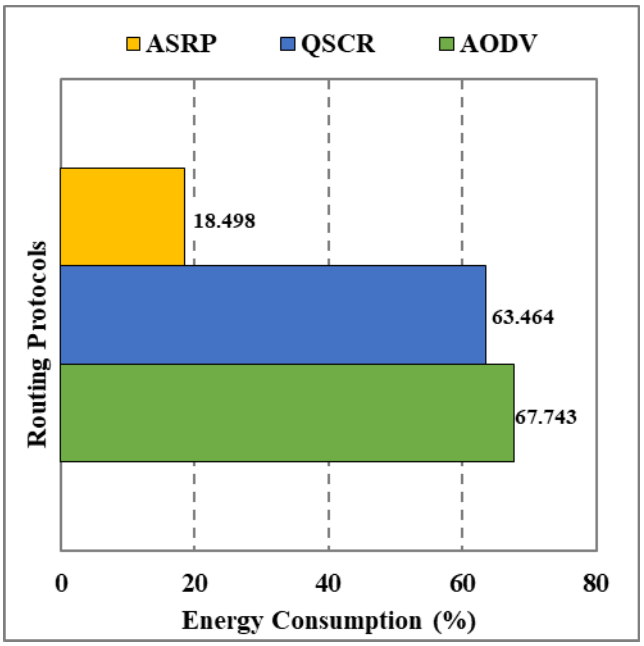

Figure 4 Energy Consumption Results

For AODV, the notable increase in energy consumption, which averages 67.743%, is significantly influenced by its inherent disadvantage related to delayed packet delivery. Frequent route discoveries and potential failures require substantial energy resources, leading to increased consumption. As network size expands, these inefficiencies compound, necessitating more energy to maintain network stability and flow of communication, thus escalating overall consumption. QSCR also shows an upward trend in energy usage, averaging 63.464%. This increase aligns with its challenge of managing high node mobility, which often leads to frequent route recalculations and higher energy demands to maintain effective communication pathways. Each recalculation impacts timely data transmission and increases the energy footprint of the routing process.

Table 5 Energy Consumption Result Values

No. of Drones	AODV (%)	QSCR (%)	ASRP (%)
50	58.567	52.093	8.459
100	60.135	54.494	10.168
150	61.905	57.741	12.611
200	64.326	60.759	15.378
250	66.685	63.192	17.649
300	68.725	65.149	19.768
350	70.764	67.065	21.998
400	73.043	69.089	24.129
450	75.521	71.342	26.294
500	77.762	73.713	28.525
Average	67.743	63.464	18.498

ASRP demonstrates a considerably lower average energy consumption of 18.498%. This efficiency stems from ASRP's robust performance even in adverse network conditions, a vital advantage of the protocol. By maintaining high efficiency and minimizing disruptions in the data flow, ASRP reduces the need for repetitive route recalculations and excessive signaling. The protocol's ability to sustain connectivity and ensure consistent data delivery with minimal energy expenditure underlines its suitability for large-scale, energy-conscious network deployments. This characteristic is critical in extending drone networks' operational duration and reliability, particularly when power availability is a limiting factor.

4.5. Link Stability

Figure 5, "Link Stability Results," provides a comparative analysis of how AODV, QSCR, and ASRP maintain communication link stability across increasing numbers of drones, with stability measured in milliseconds (ms). This metric is crucial for understanding the network's reliability as the number of participating nodes scales up.

AODV shows declining link stability, with an average stability value of 4.339 ms, as indicated in Table 6. This decline can be linked to the lack of a practical route caching mechanism in AODV. The protocol's inability to store and efficiently reuse routes results in frequent rediscovery processes. This constant need to establish new routes disrupts the continuity of connections, significantly reducing link stability as the number of drones increases.

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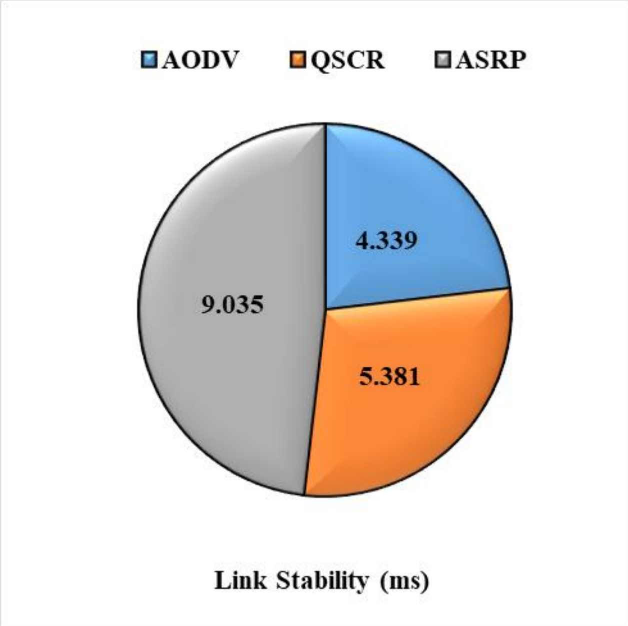

Figure 5 Link Stability Results

QSCR exhibits slightly better stability, averaging 5.381 ms, as detailed in Table 6. However, the greedy nature of its routing algorithm introduces limitations. Greedy routing often relies on the nearest cluster head, which may not always be ideally positioned toward the destination. This misalignment can lead to suboptimal routing paths that strain the network, reducing overall stability and causing fluctuations in link reliability as drone positions change.

Table 6 Link Stability Result Values

No. of Drones	AODV (ms)	QSCR (ms)	ASRP (ms)
50	5.368	6.380	9.672
100	5.076	6.197	9.559
150	4.905	5.929	9.440
200	4.677	5.652	9.297
250	4.474	5.443	9.165
300	4.254	5.246	9.026
350	4.011	5.045	8.842
400	3.771	4.829	8.643
450	3.545	4.632	8.453
500	3.310	4.458	8.249
Average	4.339	5.381	9.035

ASRP shows a significantly higher average link stability of 9.035 ms, as shown in Table 6. The protocol's broad compatibility with various network architectures is a crucial advantage, allowing it to adapt seamlessly across different environments. ASRP's ability to integrate smoothly with a wide range of network types ensures that communication links are maintained consistently without the interruptions seen in other protocols. This robustness in link stability makes ASRP particularly suitable for dynamic drone networks, where maintaining continuous and reliable communication is critical to operational success.

4.6. Hop Count Analysis

Figure 6, "Hop Count Analysis," evaluates the number of hops required for data packets to reach their destination across varying numbers of drones. The X-axis represents the number of drones in the network, ranging from 50 to 500, while the Y-axis shows the average hop count, reflecting the efficiency of the routing protocols.

AODV demonstrates a high and consistent average hop count of 10.059, as seen in Table 7. Its inability to handle high-speed network demands effectively hinders the protocol's performance. This limitation forces the protocol to use longer, less efficient paths, resulting in more hops. QSCR, with an average hop count of 9.031, is also affected by its routing algorithm's sensitivity to the discount factor. This sensitivity leads to suboptimal routing decisions, particularly in more extensive networks, where it struggles to consistently choose the most direct paths, thereby increasing the hop count.

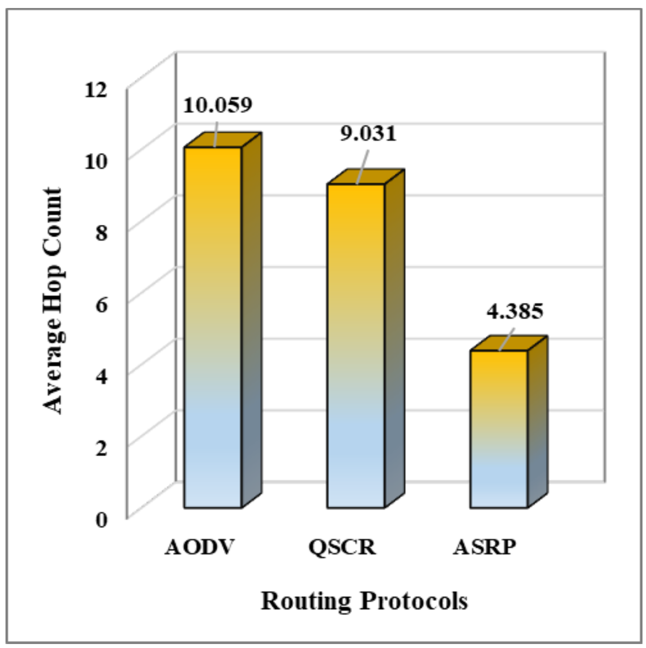

Figure 6 Hop Count Analysis

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Table 7 Hop Count Analysis Result Values

No. of Drones	AODV	QSCR	ASRP
50	9.969	8.834	3.607
100	9.992	8.896	3.903
150	10.010	8.946	4.084
200	10.035	8.988	4.222
250	10.055	9.025	4.373
300	10.072	9.059	4.512
350	10.090	9.091	4.641
400	10.107	9.123	4.747
450	10.124	9.156	4.839
500	10.141	9.188	4.921
Average	10.059	9.031	4.385

ASRP significantly reduces the average hop count to 4.385, as indicated in Table 7. The protocol's design optimizes for long-distance routing, ensuring that data packets traverse the network using the most direct paths available. This optimization minimizes the number of intermediary hops, improving overall network efficiency and performance. The substantial reduction in hop count achieved by ASRP highlights its effectiveness in environments requiring fast and reliable data transmission, making it a superior choice for managing complex and large-scale drone networks.

5. CONCLUSION

ASRP sets a new standard for managing the complexities of DANETs. By addressing the critical challenges of scalability and routing efficiency, ASRP ensures that drone networks remain stable, efficient, and capable of adapting to dynamic environments. The protocol employs a design that continuously adjusts to changing conditions within the network, ensuring optimal performance. This approach significantly enhances communication reliability and reduces energy consumption, which is crucial for extending the operational life of drones in various scenarios. Simulation results confirm the protocol's ability to deliver improved data transmission efficiency while minimizing resource usage, underscoring its effectiveness in managing large-scale drone networks. ASRP's capabilities suggest a strong foundation for future advancements in drone communication, offering a reliable and scalable solution for increasingly demanding applications. Adopting ASRP within DANETs promises to support more complex missions by maintaining consistent network performance, even under challenging conditions. This advancement addresses current limitations and opens the door to further innovation in autonomous drone networks, ensuring they can meet the evolving demands of modern operations.

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