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Original Article

Optimizing Quality of Service and Energy Efficiency in Hazardous Drone Ad-Hoc Networks (DANET) Using Kingfisher Routing Protocol (KRP)

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Abstract *- Communication networks in hazardous environments present additional problems to problems already encountered in terrain and environment, often unpredictable and extreme. The time and reliability of data communication for critical operations become necessary. When traditional networks fail, there is a need for real-time communication, and this is exactly the utility of Drone Ad-hoc Networks (DANET). DANET is relevant in search and rescue, surveillance, and emergency response. Routing in DANET has particularly difficult characteristics in that continuous coverage and stable communication links are hard. On top of this, high drone mobility, frequent network topology changes, and scarce power resources make it difficult to realize reliable data transmission with low power consumption simultaneously. To address them, presenting the Kingfisher Routing Protocol (KRP). The network modifies paths over time according to real-time conditions. This is a dynamic problem. Based on continuously monitored position, signal strength, and network density, the protocol dynamically reconfigures routes that maximize energy efficiency while providing Quality of Service (QoS). KRP uses advanced algorithms based on the behavior of kingfishers that maximize efficiency by making drones pick the best routes (load balancing and energy efficiency, respectively). Link failures can be detected, and recovery can be made robust through the protocol incorporation of pre- and post-mechanisms that handle them. Simulation shows that KRP achieves significant performance improvement (critical performance indicators: packet delivery ratio, latency, energy efficiency, and link stability). The enhancement of these outlines KRP's capability to enhance DANET activities within harsh environments, providing dependable and energy-efficient communication.*

Keywords *- Drones, Ad-hoc Networks, Disaster Management, Energy Efficiency, Routing Protocol, Kingfisher Routing Protocol.*

1. Introduction

The ability of Drones Ad-hoc Networks (DANET) to form self-organizing drones capable of a more tolerant communication system is expected to change various industries. Such a network can self-form and respond to real-time performance changes in complex environments. Thus, DANETs have a lot of promise in boosting the overall effectiveness of smart cities, especially in traffic surveillance and management, checking intracultural health and security, etc. DANETs can improve precision farming approaches by delivering and sharing details of crop and climate scouting [2]. Further embracing and embedding new technologies like AI and ML in DANET's performance and usability in various industries are ensured [3].

Hazardous DANET corresponds to drones operating in conditions where conventional communication poses great difficulties due to the prevailing circumstances. Communication in these networks must be based on protocols allowing end-to-end connectivity despite cyclic interconnectivity interruption and dynamic network structure [4]. Scalability and adaptability are important to failures; the failure of one or more locations in the network does not disrupt the data flow. The energy resources of drones must be managed carefully; therefore, the routing paths that the protocols must use must be optimized to reduce energy usage. Protocols need to ensure latency while at the same time ensuring that they support the scalability for increased numbers of drones without degrading the performance of the network [5]. Reducing energy usage while providing consistent and reliable links to the other nodes increases the network's lifetime.

Routing in the future of DANET thus holds the next big chance of being developed by incorporating new things such as machine learning and artificial intelligence. These technologies improve routing protocols by estimating topological changes influenced by drone motion and environmental conditions [6]. Algorithms used in predictive technology enhance routing, minimizing latency and increasing the efficiency of the network. Since drones have restricted battery life, energy-efficient routing methods require significant focus. Reducing power consumption while preserving dependable links enhances the network's functionality and useful life [7]. The technological development in the sensors used and the real-time monitoring of the networks allow for an easier and more detailed understanding of the status of the network at times of routing. The evolution of such technologies shows that DANET can be made more effective, versatile, and capable of meeting the needs of a great field of many applications, from smart cities to environmental sensing [8, 9].

1.1. Problem Statement

With limited battery life for drones, energy consumption management is an important challenge. Drones use routes excessively, often requiring rerouting and retransmitting lost data, which can translate into inefficient routing protocols. It shortens the life of individual drone operations and reduces the efficiency of the entire network. Energy efficiency and reliable data transmission are challenging for the high mobility and dynamic DANETs. Environmental factors like speed airflows can make drones suddenly change direction and further trash their energy resources. Given the continuous route adjustment and corresponding increase in energy consumption required for DANETs, energy-efficient routing protocols are needed to address the challenges associated with DANETs.

1.2. Motivation

The limited battery life of drones directly impacts their operational longevity and effectiveness in DANETs; therefore, energy consumption is an important concern. Both routing protocols and the design of the drone networks can lead to inefficient routing, exacerbating energy consumption, and thus, rapid drone battery depletion and short network lifetime. Individual drones use high energy, which can cause network partitioning and reduce coverage. One more can affect the stability and function of the network as a whole. So, it is necessary to develop energy-efficient routing algorithms to conserve energy usage with high routing efficiency.

It is time for these algorithms to focus more on energy-aware path selection load balancing and to reduce the rate of unnecessary data transmission. Such strategies cannot only greatly extend the operational lifespan of the drones themselves, prolong mission endurance, and sustain network performance, but they have also been proven to help enhance range. At the application level, the ability of DANETs to provide efficient energy management in these routing protocols is essential to maximize the utility and effectiveness of DANETs in many applications as the network continues to function and remain reliable over a prolonged period, where recharging or replacing batteries is either infeasible or impractical.

1.3. Objective

This paper aims to present a bio-inspired optimization routing protocol that concurrently optimizes energy consumption and routing efficiency in DANETs. Because drones have limited battery life, energy-efficient routing is vital to extend the network's operational lifespan. Inspired by nature's energy-efficient process, the proposed protocol will use algorithms that prefer energy conservation. The protocol seeks to extend the computation operational lifespan of drones and the overall network by optimizing path selection and load balancing based on real-time energy metrics. This approach will be validated by simulations and field trials, and it will show how this can maintain an acceptable balance of energy consumption versus the routing efficiency and increase the sustainability of DANETs in energy-constrained environments.

2. Literature Review

"EV-Drone Hybrid Delivery" [10] integrates electric vehicles and drones for optimized package delivery. Vehicles transport drones to strategic locations, where drones take over for last-mile delivery. Drones follow predetermined routes using GPS, while vehicles act as mobile hubs. Real-time data optimizes routes based on traffic and weather. This hybrid approach enhances efficiency and reduces delivery times by leveraging the strengths of both transportation modes. The issues in "Heterogeneous Multi-Drone Routing (HMDR)" [11] are solved with an iterative two-phase approach.

The first part solves minor optimization problems, assigning drones to routes based on capacity and demand. An approximate second version of each tour is produced by reassigning drones and reassigning routes through local search. The method reduces travel distance and distributes load among drones in such a way as to arrive in an optimal or near-optimal state. "Swarm Route Optimization" [12] is used to optimize the efficiency of UAVs in workload constraints. UAVs are modeled as ants exploring routes using the Ant Colony Optimization framework. The Traveling Salesman Problem formulation guarantees each UAV's complete deliveries while minimizing travel distance. At each time step, load balancing is done per the algorithm, considering battery life and payload capacity. Pursuing this idea of Adaptive Intelligence means that paths are iteratively explored to refine paths to adapt to changing conditions and workloads.

"Stock-taking Drone Optimization" [13] optimizes storage space usage and automatically optimizes stock-taking routes and warehouse charging station locations. The placement algorithms minimize downtime and ease of access. The routing algorithms are advanced, and paths are calculated efficiently, adjusting as real-time data is incoming. Such integration endows uninterrupted stock-taking with increased inventory accuracy and operation efficiency. "Multi-Trip Truck-Drone Data Routing" [14] is a robust optimization technique that optimizes information flow in multi-trip truck drone systems. After they deliver, drones collect data and route it into a central system. Dynamic network conditions and historical data are used on which the algorithm adjusts paths. Data is transmitted reliably via multi-hop communication and adaptive routing for operational efficiency. “Smart Drone Recharge & Mission Plan" [15] autonomously managing drone power and flight paths. Battery levels are monitored, and recharging stations are shared in a broadcast manner so they can navigate them if needed. Energy replenishment is strategically placed via recharging stations. Sensor data and communications network data from aerial drones are improved, enabling drones to resume missions with optimized flight paths that balance energy consumption and mission requirements. This process operates within operational efficiency without the need for human intervention.

"5G UAVs for Opportunistic Networking" [16] integrated with UAV improve energy efficiency for opportunistic networking. UAVs are connected to ad-hoc networks dependent on their real-time conditions. Inventory of the devices is integrated with connectivity and data routing management, particularly using 5G features for more reliable networks and less energy consumption by advanced algorithms. The research optimizes energy usage in such a way that it extends flight times and assists in improving network performance. “Hybrid MGO-JAYA Clustered Routing” [17] was developed to improve efficient data transmission by combining Multi-Objective Genetic Optimization (MGO) with the JAYA algorithm.

Proximity and energy level information is integrated into cluster UAVs. JAYA optimizes clusters, and MGO forms clusters. It adapts to a network change and guarantees efficient and reliable data transmission. In dynamic environments, the hybrid approach also improves network performance. “Adaptive Truck-Drone Delivery” [18] is a multi-objective optimization algorithm that performs collaborative delivery services. Based on real-time data, resources are dynamically allocated to trucks and drones. Drones take the final delivery leg, operating as the final leg from the trucks to the address. The algorithm feature adjusts the allocation continuously to find the optimal delivery time, the minimum energy, and the minimum costs. This approach allows for an adaptive efficiency and reliability of the delivery network.

"Hybrid Multi Objectively Truck Drone Routing" [19] combines truck and drone coordination and ad-hoc routing with multi-objective optimization. Routing scenarios are evaluated with Genetic Algorithms and Particle Swarm Optimization. Drones in ad hoc networks rely on trucks for communication. The system routes as the situation is, and there is almost no room for error in delivering the product. This hybrid approach enhances performance in the decentralized environment. "SWEEPER" [20] employs a secure waterfall routing strategy for energy-efficient data transmission in FANETs. Datam, a dynamic topology formed by UAVs exchanging status with each other, passes data from higher energy to lower energy nodes. Secure communication is achieved through robust encryption and efficient communication with adaptive transmission power control. It works as a reliable and energy-saving protocol that adapts to network changes. "ACO-Based Drone Routing" [21] is proposed for hazardous waste collection in dynamic locations. Like course paths, drones use pheromone trails to explore, updating above them based on route quality. It works iteratively: it explores, then it exploits its previous paths. Efficient and safe waste collection is ensured by real-time adjustments that consider changing circumstances. This approach helps improve route efficiency and reliability in logistics scenarios with complex demand.

"Ad-hoc On-demand Distance Vector (AODV)" [22] constructs routes by originating RREQ packets, which it receives at intermediate or destination nodes with valid routes. It will not even require constant routing and retaining of resources. Network attacks in broadcast communication, e.g., blackhole, wormhole, and Sybil attacks, can effectively undermine this protocol's capabilities. Thus, AODV is inappropriate to support applications with required data delivery times. The overhead caused by maintaining routes in highly dynamic environments curtails overall network performance. However, the overhead of setting up routes is high for small data packets, so the protocol is inefficient.

In "Q-learning-based Secure and Reliable Clustering Routing (QSCR)" [23], learning models are updated, and the network is stabilized with frequent control messages sent to manage clusters. This has the side effect of increasing network traffic, affecting overall performance, and causing security vulnerabilities with additional control transmissions. The QSCR may not respond quickly enough to node failures, which can be problematic for handling network stability. It becomes a synchronization problem, making the drones work separately to store information, but it needs to be synchronized. Second, the implementation of the protocol is also complicated by choosing an appropriate network and learning rate independent of the stable dynamics of the network.

2.1. Technological Gaps

Methods for optimizing energy consumption and routing efficiency, such as EV-Drone Hybrid Delivery and ITPO-MDR, present notable challenges. Extensive computational requirements and complex coordination between drones and vehicles often lead to inefficiencies and delays. Hurdles exist in the use of such potential technologies, including Swarm Route Optimization and Smart Drone Recharge and Mission

Plan, in terms of accurate real time data acquisition and the requirement of sophisticated algorithms for dynamic adjustment. Existing solutions lack optimal energy vs communication performance tradeoff, especially in environments with varying environmental conditions and high mobility. While providing reliable communication and timely decision-making, proper protocols are desired which are energy efficient.

Table 1. Comparative analysis of energy-efficient routing methods

Name	Methodology	Merits	Demerits	How It Affects Drone Communication
EV-Drone Hybrid Delivery [10]	Integrates electric vehicles and drones for optimized package delivery.	Enhances efficiency, reduces delivery times, and leverages the strengths of both transportation modes.	Complex coordination is required between vehicles and drones.	Communication delay due to complex coordination.
ITPO-MDR [11]	Iterative two-phase approach for heterogeneous multi-drone routing.	Minimizes travel distance and balances load among drones.	Requires extensive computation for iterative refinement.	High computational overhead affecting communication.
Swarm Route Optimization [12]	Uses ACO-DTSP algorithm for UAV swarm efficiency under workload constraints.	Balances workload to ensure efficient delivery.	Initial setup and tuning of pheromone trails can be complex.	The initial communication setup is complex.
Stock-taking Drone Optimization [13]	Strategic location of charging stations and optimized drone routes.	Continuous operation improves inventory accuracy and efficiency.	Initial analysis and setup of charging stations are time-consuming.	Delays in communication during the initial setup phase.
Multi-Trip Truck-Drone Data Routing [14]	Robust optimization for data flow in multi-trip truck-drone systems.	Reliable data transmission enhanced operational efficiency.	Dependent on real-time data and historical analytics.	Communication issues if real-time data is not accurate.
Smart Drone Recharge & Mission Plan [15]	Autonomous power and flight path management for drones.	Maintains operational efficiency and reduces the need for human intervention.	Relies on accurate pre-programmed GPS coordinates for recharging stations.	Communication issues if GPS data is inaccurate.
5G UAVs for Opportunistic Networking [16]	Integration of 5G technology for enhanced energy efficiency and communication.	Optimizes energy usage, extends flight times, and improves network performance.	High reliance on 5G network infrastructure.	Affected by the availability of 5G infrastructure.
Hybrid MGO-JAYA Clustered Routing [17]	Combines MGO with the JAYA algorithm for efficient data transmission in clustered UAVs.	Enhances network performance and adapts to dynamic environments.	Complexity in clustering and route optimization.	High complexity in maintaining optimal communication.
Adaptive Truck-Drone Delivery [18]	Multi-objective optimization for dynamic resource allocation between trucks and drones.	Increases delivery efficiency and reliability.	Requires real-time data and continuous adjustments.	Communication delays if real-time data is lacking.
Hybrid Multi-Objective Truck-Drone Routing [19]	Multi-objective optimization and ad-hoc routing for truck-drone coordination.	Ensures efficient delivery operations in decentralized environments.	Complex adaptive and decentralized routing protocols.	Communication can be affected by complex routing protocols.
SWEEPER [20]	Uses secure waterfall routing for energy-efficient data transmission in FANETs. Data flows from higher to lower-energy nodes.	Secure, energy-efficient communication, reliable adaptation	Complexity in managing encryption and power control	Adaptive adjustments can cause temporary delays

ACO-Based Drone Routing [21]	Uses Ant Colony Optimization for routing drones in hazardous waste collection. Paths are refined using pheromone trails.	Efficient, reliable route optimization, real-time adaptation	Iterative process may be computationally intensive	High computational demands can delay communication

3. Kingfisher Routing Protocol

Kingfisher Routing Protocol (KRP) is designed to be inspired by the observational behavior of kingfishers, their ability to see things closely, and the precision of their hunting techniques. KRP is attempting to mimic these natural behaviors to increase the efficiency and reliability of DANET. The protocol is broken into phases, each dealing with a specific problem in drone communication, such as route discovery, data transmission, and optimizing data communication. Advanced mathematical models and algorithms are employed to optimize drone positioning, neighbor discovery, route selection, and error handling, significantly improving the robustness and adaptivity of the network service provided by KRP.

3.1. Perching Phase

The perching phase represents the first step towards the efficient drone communication routes in the KRP, serving as the initialization of the KRP for DANET. True kingfishers perch above high objects, peering at the sight of prey, describe down to the water for pursuit. During the Perching Phase of DANET, drones visit (or perch) their area of interest to determine network conditions and locate nearby nodes. This section considers mathematical forms of the Perching Phase of KRP.

On the other hand, drones are in the Perching Phase and realize their initial positions on the network using positioning algorithms. Depending on the available hardware and environmental constraints, proximity-based methods are used. The Trilateration method is one common algorithm that defines a drone's position by triangulating (measuring) its distance to 3 or more known anchor points. It is expressed as Equation (1).

$$d_{i,j} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 + \left(z_i - z_j\right)^2} \qquad (1)$$

Where $d_{i,j}$represents the distance between drone i and anchor point j, and (x_i, y_i, z_i)denotes the coordinates of the drone i.

Therefore, drones must discover neighboring nodes within their communication range to establish communication links. Neighbor Discovery Probability $(P_{discover})$ expresses the probability that a nearby drone is detected successfully, given its signal strength and environmental condition. Equation (2) is the model of this probability modeled as probabilistic distribution, for example, Gaussian distribution.

$$P_{discover} = e^{-\frac{(d-\mu)^2}{2\sigma^2}} \qquad (2)$$

Where d represents the distance between drones, and μ and σ denote the mean and standard deviation of the signal strength distribution, respectively.

During the Perching Phase, drones must conserve energy by actively searching the environment for neighbouring nodes. The positioning and communication activities of the Energy Consumption Model are estimated to consume the energy needed to engage in those activities. To this end, one linear energy consumption model defined by Equatio (3) can be utilized, in which energy consumption $(E_{consume})$ is proportional to the distance traveled (d_{travel}) and the data transmission rate $(R_{transmit})$.

$$E_{consume} = \alpha \times d_{travel} + \beta \times R_{transmit} \qquad (3)$$

Where α and β represent the energy consumption coefficients.

The effectiveness of the communication links during the Perching phase is highly dependent upon the drone density in the network. Network Density Estimation techniques investigate the drone spatial distribution to roughly evaluate the overall network density. The second approach is to divide the space into regions of a drone for which every point in its region is closest to that drone. The Voronoi cell area $(A_{Voronoi})$ can be calculated as Equation (4).

$$A_{Voronoi} = \frac{1}{3}\sum_{i=1}^{n} A_i \qquad (4)$$

Where A_i represents the area of the Voronoi cell associated with drone i, and n denotes the number of drones in the network.

Optimizing the communication range of drones is essential for ensuring reliable connectivity while conserving energy. The Communication Range Optimization algorithm adjusts the transmission power of drones based on the network density and Signal-to-Noise Ratio (SNR). One approach is to maximize the coverage area.$\left(A_{coverage}\right)$ within a specified SNR threshold $(SNR_{threshold})$ mathematically expressed as Equation (5) and Equation (6).

$$A_{coverage} = \frac{\pi}{4} \times (d_{max})^2 \qquad (5)$$

$$d_{max} = \sqrt{\frac{P_{transmit} \times G_{transmit}}{N_0 \times SNR_{threshold}}} \quad (6)$$

Where $P_{transmit}$ and $G_{transmit}$ denote the transmission power and antenna gain, respectively, and N_0 represents the noise power spectral density.

A probability of having a connection to neighboring drones is essential in developing a way to measure how well a network is likely to perform. The Connectivity Probability ($P_{connect}$) looks at the strength of the signal, possible interference with the signal and the prevailing environment to determine the possibility of data transmission. The first approach is to define $P_{connect}$ in terms of Equation (7) with the received signal power ($P_{received}$)and the interference power $\left(P_{interference}\right)$.

$$P_{connect} = 1 - \frac{P_{interference}}{P_{received}} \quad (7)$$

Where $P_{interference}$ can be calculated based on interference from neighbouring drones and external sources.

3.2. Neighbor Discovery

The neighbouring discovery is a critical stage corresponding to the KRP for DANET and aims to create links between drones. Inspired from the social behaviour of kingfishers, which are generally found near water bodies, this phase lets drones ascertain the loci of the next connected nodes to be approached. Signal strength between two drones is an important factor that defines the feasibility of its discovery by the other drone.

The signal strength model (S_{model}) describes the amount of received signal power ($P_{received}$) at some distance (d) between the two drones, transmitting and receiving. According to the inverse square law of the model, which is expressed as Equation (8).

$$S_{model} = \frac{P_{transmit} \times G_{transmit} \times G_{receive}}{(4\pi \times d)^2 \times L} \quad (8)$$

Where $P_{transmit}$ is the transmission power, $G_{transmit}$ and $G_{receive}$ are the antenna gains of the transmitting and receiving drones, respectively, and L is the path loss factor.

The probability of successful neighbour detection (P_{detect}) is the cumulative result of success factors in performing neighbour detection, such as signal strength, interference and environmental factors. It is possible to use a probabilistic model to calculate P_detect depending on the received signal, the power, $P_{received}$ and the detection threshold $P_{threshold}$ as it is shown in Equation (9).

$$P_{detect} = 1 - e^{-\frac{P_{received}}{P_{threshold}}} \quad (9)$$

Where $P_{received}$ is obtained from the signal strength model and $P_{threshold}$ represents the minimum required signal power for successful detection.

Drones periodically broadcast beacon signals to announce their presence and facilitate neighbour discovery. The beacon interval (T_{beacon}) determines the frequency at which drones transmit beacon signals. Optimizing T_{beacon} is crucial for balancing the tradeoff between neighbor discovery efficiency and energy consumption. A common approach is to adjust. T_{beacon} dynamically based on network density and traffic load. Equation (10) computes T_{beacon}.

$$T_{beacon} = \frac{1}{\lambda_{beacon}} \quad (10)$$

Where λ_{beacon} represents the beacon rate, determined based on network parameters such as the number of active drones and communication range.

Every drone also holds a neighbour table in order to track the ID, received signal strength and the ability of the neighbours to communicate with other systems. Neighbour table management consists of modifying and altering this data for optimum neighbour identification and routing. For instance, with methods like the Weighted Moving Average (WMA), the signal's strengths can be calculated based on dynamic signal strength measurements. Equation (11) provides the over all formula for computing the weighted average of signal strength.

$$S_{avg}(t) = (1 - \alpha) \times S_{avg}(t-1) + \alpha \times S_{new}(t) \quad (11)$$

Where $S_{avg}(t)$ represents the weighted average signal strength at time t, $S_{new}(t)$ is the latest signal strength measurement, and α is the smoothing factor.

Drones have the freedom to place the antennas practically where the neighbouring drones can be easily discovered in the shortest time compared to conventional techniques. It provides the drones with the ability to improve their transmission and reception in a certain direction. The beamforming gain (G_{beam}) can be obtained from the antenna pattern and the beamforming angle, as defined in Equation (12).

$$G_{beam} = G_{max} \times sinc^2(\theta) \quad (12)$$

Where G_{max} is the maximum antenna gain, and θ is the beamforming angle.

Especially when the amount of energy available is fairly limited, there is a particular need to discover the neighbours while simultaneously operating with minimum energy expenditure for smooth link connection. An energy-aware discovery threshold ($P_{energy\_threshold}$) is evaluated with Equation (13). Instead, it is preprogrammed and dynamically adjusted depending on the remaining energy level of the drone, $E_{remaining}$.

$$P_{threshold} = P_{default} - \frac{E_{remaining}}{E_{total}} \times P_{adjust} \tag{13}$$

Where $P_{default}$ is the default detection threshold, $E_{remaining}$ represents the remaining energy, E_{total} is the total energy capacity, and P_{adjust} is the adjustment factor.

3.3. Keen Observation

In the KRP planning for DANET, the Keen Observation phase is comparable to the scanning behaviour of kingfishers in search of their food. Drones are constantly seeking information about the current state of a network and searching for the best way to get the data to its final user. This phase encompasses mathematical models and solutions to route discoveries for quality and timely transmission of information in a network. Drones need a metric by which to measure the quality of possible routes to help identify which routes to discover. The Q_{route} metric incorporates items that mark different routes depending on latency, bandwidth, reliability, etc. One of the used ways is to define Q_{route} as the sum of different metrics weighted in proportion to their values given in Equation (14).

$$Q_{route} = (w_1 \times Latency) + (w_2 \times Bandwidth) + (w_3 \times Reliability) \tag{14}$$

Where w_1, w_2 and w_3 are the weights assigned to each metric, reflecting their relative importance.

Nodes of the drones use the Link State Advertisement (LSA) messages to share information about their neighbouring nodes as well as the topology of the network. These drones dynamically transmit their LSAs, which include their identity, available resources and link-quality estimations from time to time. In Equation (15), It shows the LSA format, and it consists of fields of sender ID (ID_{sender}), receiver ID ($ID_{receiver}$) and link quality (Q_{link}).

$$LSA = (ID_{sender}, ID_{receiver}, Q_{link}) \tag{15}$$

Dijkstra's algorithm is as old as the routing algorithms, and the drones employ it to investigate the shortest pathways to the target destination nodes from the received LSAs. The algorithm is used to cycle through the neighboring nodes, and the cost of getting to that particular node and the path with the minimum cost is then selected. The minimum cost of the path from the source node to each of the destination nodes is defined as ($C_{shortest}$) in Equation (16).

$$C_{shortest}(v) = min\{C_{shortest}(u) + w(u, v)\} \tag{16}$$

Where $C_{shortest}(v)$ represents the cost of reaching node v, $C_{shortest}(v)$ is the cost of reaching the predecessor node u, and $w(u, v)$ denotes the weight of the edge between nodes u and u.

Drones employ a route discovery timer to mitigate routing overhead and control message propagation. ($T_{discovery}$) to limit the duration of route discovery processes. The timer specified in Equation (17) determines the maximum duration for which a drone actively searches for routes before considering alternative strategies or revisiting the process later.

$$T_{discovery} = Random(T_{min}, T_{max}) \tag{17}$$

Where $Random(T_{min}, T_{max})$ generates a random value within the specified range.

Once multiple potential routes are discovered, drones employ path selection strategies to choose the most suitable route for data transmission. These strategies consider route quality metrics, available resources, and network dynamics. The routes with lower latency and higher reliability are calculated using Equation (18).

$$P_{select} = \frac{1}{Q_{route}} \tag{18}$$

Where P_{select} denotes the route selection priority level, and it will be inversely proportional to Q_{route}.

3.4. Hovering Phase

The Hovering Phase in the KRP for DANET chick corresponds to when the kingfisher hovers over water before taking its target. Likewise, in KRP, satellites remain above probable paths, anticipating various aspects to choose the best approach for data communication. The fourth phase is focused on mathematical calculations and selecting the route that will be considered most effective and safe. Consistency or stability of routes is an important factor when choosing routes, and the data transmission should be consistent. The route stability metric S_{route} reflects the likelihood of using particular routes and the network conditions for the route as analyzed based on historical information. Equation (19) define S_{route} that involves the computation of Exponentially Weighted Moving Averages (EWMA) of route quality metrics.

$$S_{route}(t) = (1 - \alpha) \times S_{route}(t - 1) + \alpha \times Q_{route}(t) \tag{19}$$

Where $S_{route}(t)$ represents the route stability at time t, $Q_{route}(t)$ is route quality metric at time t, and α is the smoothing factor.

Self-organising drones use load-balancing methods to select routes that allow traffic to be evenly distributed across available routes. While navigating, drones have the option of using metrics, including link utilization and packet loss rate, to determine the load that various routes are handling. The most used is the load balancing ratio ($L_{balance}$), which is calculated using the bandwidth of the current traffic load and is provided in Equation (20).

$$L_{balance} = \frac{B_{available}}{B_{current}} \tag{20}$$

Where $B_{available}$ is the available bandwidth and $B_{current}$ is the current traffic load on the route.

The route selection algorithm is used to identify criteria and processes by which the best route among the available ones is to be chosen. However, depending on the type and need, routing techniques can be implemented in different networks, such as shortest path routing, load-aware routing, or even QoS routing. Of these, the Weighted Sum Model set out in Equation (21) is frequently applied to additively integrate several route metrics.

$$Score_{route} = \sum_{i=1}^{n} w_i \times M_i \tag{21}$$

Where $Score_{route}$ represents the overall score of the route, w_i is the weight assigned to the metric M_i, and n is the total number of metrics considered.

In cases where specific Quality of Service (QoS) demands dictate reception, drones offer routes that meet particularly prescribed QoS needs, either in terms of minimal delay, maximal jitter, or secured bandwidth. The QoS-aware routing algorithms are characterized by the fact that they seek to select given routes while operating with certain QoS limitations. Because of this, Equation (22) can be used in dynamically adapting a route selection depending on the actual achieved QoS and negotiations.

$$P_{select} = \begin{cases} 1 & if\ QoS_{constraints}\ are\ satisfied \\ 0 & otherwise \end{cases} \tag{22}$$

Some routes based on drones may include a diversity of possible physical paths, intermediate nodes, or communication links to improve network reliability. It is agreed that route diversity assists in reducing the effect of link failures, congestion, and other network anomalies. In this research, Diverse Path Selection, defined in Equation (23), aims to choose routes supporting path diversity and other routing criteria.

$$Diversity_{route} = \frac{Number\ of\ diverse\ paths}{Total\ number\ of\ paths} \tag{23}$$

In dynamic networks, routes are not always stable and may exhibit varying levels of performance as a result of factors such as traffic distribution, network status, or configuration. Selected paths of drones are perpetually reassessed for these changes in order to alter their routing decisions on a dynamic basis. Route-by-route stability measures assess stability, loads, and Qo S parameters and initiate a route update or a change when required.

3.5. Dive Preparation

The Dive Preparation phase may be considered to correspond to the Sign posting phase of the KRP for DANET. It represents a kingfisher bird changing its wings' position before diving into the water. Similarly, in KRP, the drones log data transmission requesting the formation of the selected route and required configuration parameters. This phase provides the mathematical tools and techniques to properly erect the right communication channel. Prior to data transmission, drones have some overhead, including pathway establishment processes such as signaling, handshake, and negotiation. The route setup overhead (O_setup) may possibly be determined dependent on the control packets taken during the process of route establishment mathematically described in Equation (24).

$$O_{setup} = N_{packets} \times T_{packet} \tag{24}$$

Where $N_{packets}$ represents the number of control packets exchanged and T_{packet} is the average time taken to transmit a single packet.

For the purpose of keeping the route effector and trustworthy, drones use route validation procedures to identify and fix probable routing errors or discrepancies. Route validation checks for the accuracy of the rout information, confirmation of the absence of loops in all routes possible, and detection of routing irregularities. The first and second solution is to use the route validation metric, calculated as a value given by the formula (25) representing the validity and quality of the established route.

$$M_{validation} = \frac{Number\ of\ valid\ routes}{Total\ number\ of\ routes} \tag{25}$$

Drones also keep and refresh the paths during data transmission in case of areas related to network conditions or path failure. Route maintenance is the resources used to monitor, update, or repair a route, which is termed $O_{maintenance}$. The maintenance overhead is computed using Equation (26) and involves the frequency of route maintenance jobs and the corresponding computational and relay expenses.

$$O_{maintenance} = F_{maintenance} \times C_{operation} \tag{26}$$

Where $F_{maintenance}$ represents the frequency of route maintenance operations and $C_{operation}$ denotes the average cost of a maintenance operation.

Drones could use channel encoding to transmit their data packets through the set channel with added privacy concerns, hence securing their data as it transmits. The overhead for route encryption overhead ($O_{encryption}$) is the amount of time taken to perform the encryption and decryption of a message. The encryption overhead may be approximated by the drones' encryption algorithm, packet size, and processing ability. In Equation (27), the encryption process is mentioned on the basis of packet count and cost.

$$O_{encryption} = N_{packets} \times \left(C_{encrypt} + C_{decrypt}\right) \quad (27)$$

Where $C_{encrypt}$ and $C_{decrypt}$ represent the computational costs of encryption and decryption, respectively.

For those topologies that require an important level of route diversity in terms of redundancy and FT, drones compute the level of path diversity that has been set up to pinpoint the SSD or single point of failure. Strong components of connectance and connectivity that help disentangle path diversity and length of various connecting routes are also considered. Diversity associated with the known path is measured by the path diversity (D_{path}) term defined by the number of disjoint source-destination paths as defined in Equation (28).

In fault-tolerant applications, where route heterogeneity is essential, drones review the level of path diversification and determine universal bottlenecks and risks. Network redundancy analysis focuses on the topology of the system and the extent to which the topology offered by the network is diverse and flexible. The D_{path} defines the measure of diverse paths used according to the number of disjoint paths between source and destination, as shown in Equation (28).

$$D_{path} = \frac{Number\ of\ disjoint\ paths}{Total\ number\ of\ paths} \quad (28)$$

Drones incorporate methods of routing that seek to minimize latency, maximize the throughput or conserve energy to enhance the overall efficiency and effectiveness of existing routes. Exemplarily, route optimization methods alter one or more of the route characteristics, including the transmission power, routing metrics or route selection criteria, to handle the occurrence of new network conditions. The first is to apply reinforcement learning algorithms to learn and improve the route selection policies used in the past and the feedback that the operating environment provides.

3.6. Dive

The Dive phase represents the data transmission in the KRP, the moment a kingfisher plunges into the water to catch its prey. In KRP, drones initiate data transmission along the established route, delivering data packets to their intended destinations. This phase involves mathematical formulations and procedures to ensure efficient and reliable data transmission. Before initiating data transmission, drones generate data packets to be sent over the established route. The data packet generation rate $\left(R_{packet}\right)$ determines the frequency at which the source node generates data packets. Equation (29) is applied to compute R_{packet}.

$$R_{packet} = \frac{D_{total}}{T_{total}} \quad (29)$$

Where D_{total} represents the total data size to be transmitted and T_{total} denotes the total transmission time.

Each data packet incurs overhead associated with packetization, including header information, error detection codes, and sequence numbers. The packetization overhead$\left(O_{packet}\right)$ can be calculated by applying Equation (30), and it will be based on the packet size $\left(S_{packet}\right)$ and the header size (S_{header}).

$$O_{packet} = S_{packet} + S_{header} \quad (30)$$

Drones dynamically adjust their transmission power to optimize energy consumption and minimize interference based on the distance to the next hop in the route. Transmission power control algorithms aim to maintain reliable communication while conserving energy. Equation (31) adjusts the transmission power ($P_{transmit}$) based on the distance (d) between the transmitting and receiving nodes.

$$P_{transmit} = \frac{P_{max}}{d^{\alpha}} \quad (31)$$

Where P_{max} represents the maximum transmission power, and α is the path loss exponent.

To enhance the reliability of data transmission, drones may employ forward error correction techniques to detect and correct errors in received data packets. Forward Error Correction (FEC) codes add redundant information to the data packets, enabling the receiver to reconstruct the original data even if some bits are corrupted. Equation (32) calculates the FEC (O_{FEC}) which depends on the FEC code rate (R_{FEC}) and the size of the redundant information.

$$O_{FEC} = (1 - R_{FEC}) \times S_{packet} \quad (32)$$

In dynamic wireless environments, drones may experience variations in channel conditions, affecting the quality of received signals. Adaptive Modulation and Coding (AMC) techniques adjust the modulation scheme and coding rate based on channel quality metrics such as Signal-to-Noise Ratio (SNR) or Signal-to-Interference-plus-Noise Ratio (SINR). Additional overhead representing signaling and adapting modulation and coding schemes is included in the modulation and coding overhead (O_{AMC}) expressed by Equation (33).

$$O_{AMC} = S_{header} \tag{33}$$

When a drone receives data packets, it sends an Acknowledgement (ACK) back to the sender as confirmation. The acknowledgement mechanism guarantees data delivery with the aid of the sender and then can alter the transmission parameters. The overhead caused by acknowledgements can be represented by overhead introduced by acknowledgements (O_{ACK}) and depends on ACK size and the number of sent acknowledgements, as shown in Equation (34).

$$O_{ACK} = N_{ACK} \times S_{ACK} \tag{34}$$

Where N_{ACK} represents the number of acknowledgements sent and S_{ACK} is the size of each acknowledgement packet.

3.7. Underwater Pursuit

The Underwater Pursuit phase denotes the relay and forwarding in KRP. It mirrors a kingfisher's relentless pursuit of prey underwater. In KRP, drones actively relay and forward data packets to ensure successful delivery to their destinations. This phase involves mathematical formulations and strategies for efficient and reliable data relay and forwarding. When multiple drones are available to relay data packets, relay selection criteria help determine the most suitable relay nodes based on proximity, link quality, and available resources. The relay selection criteria $\left(C_{relay}\right)$ can be expressed as a weighted sum of individual metrics:

$$C_{relay} = w_1 \times Proixmity + w_2 \times Link\ Quality + w_3 \times Resource\ Availability \tag{35}$$

Where w_1, w_2 and w_3 are the weights assigned to each metric.

Upon receiving data packets, drones make forwarding decisions based on routing tables, destination addresses, and relay selection criteria. The forwarding decision algorithm determines whether to forward packets directly to the destination or relay them through intermediate nodes. One approach uses Equation (36), which selects the next best hop based on route metrics and network conditions.

$$NextHop = argmin(Q_{route}) \tag{36}$$

Where Q_{route} represents the route quality metric.

To prevent packet loss and ensure efficient data forwarding, drones employ buffer management strategies to prioritize and manage the transmission of queued packets. Buffer management algorithms adjust buffer sizes, packet drop policies, and congestion control mechanisms based on network conditions. A commonly used strategy is the First-In-First-Out (FIFO) queuing discipline, where packets are transmitted in the order they arrive. Equation (37) represents the same.

$$D_{FIFO} = \frac{N_{arrivals}}{N_{departures}} \tag{37}$$

Where $N_{arrivals}$ and $N_{departures}$ represent the number of packets arriving and departing from the buffer, respectively.

Relaying data packets consumes energy, and drones must optimize energy usage to prolong network lifetime and ensure uninterrupted operation. The relay energy consumption model estimates drones' energy while relaying packets based on transmission power, packet size, and relay distance. One approach is to use a linear energy consumption model specified in Equation (38).

$$E_{relay} = \alpha \times d_{relay} + \beta \times S_{packet} \tag{38}$$

Where d_{relay} represents the distance traveled by the relay drone, and α and β are energy consumption coefficients.

In dynamic and unpredictable environments, drones may encounter changes in network topology, link quality, or traffic patterns. Adaptive routing protocols enable drones to adjust routing decisions and forwarding strategies adaptively based on real-time observations and feedback. The adaptive routing protocol dynamically updates routing tables using Equation (39), adjusts relay selection criteria, and redistributes traffic to optimize network performance:

$$P_{adaptive} = \frac{1}{Q_{route}(n)} \tag{39}$$

Where $P_{adaptive}$ represents the priority of selecting a route based on adaptive routing criteria, and n represents the threshold time limit.

Drones employ error correction and retransmission mechanisms to cope with transmission errors and packet losses to ensure reliable data delivery. Error correction codes, such as Reed-Solomon or convolutional codes, add redundancy to data packets, enabling receivers to detect and correct errors. If errors persist despite error correction, drones initiate retransmissions to request missing or corrupted packets using Equation (40).

$$P_{retransmit} = \frac{N_{retransmissions}}{N_{total\_packets}} \tag{40}$$

Where $N_{retransmissions}$ represents the number of packet retransmissions and $N_{total\_packets}$ is the total number of packets transmitted.

3.8. Capture Phase

The Capture phase in the KRP for DANET signifies a kingfisher's successful capture of prey. In KRP, this phase corresponds to the acknowledgement of received data packets and the handling of transmission errors to ensure reliable data delivery. This phase involves mathematical formulations and procedures for effectively managing acknowledgements and handling errors. After transmitting data packets, drones wait for acknowledgements from the receiver to confirm successful delivery. The acknowledgement timeout (T_{ack}) determines the maximum duration a drone waits for an acknowledgement before considering the transmission unsuccessful and initiating error handling mechanisms. Equation (41) is applied to compute T_{ack}.

$$T_{ack} = \sum Random(T_{min}, T_{max}) \tag{41}$$

Where $Random(T_{min}, T_{max})$ generates a random value within the specified range.

The acknowledgement rate (R_{ack}) reflects the proportion of successfully acknowledged data packets relative to the total transmitted packets. Equation (42) provides insights into data transmission, reception reliability, and efficiency.

$$R_{ack} = \frac{N_{acknowledged}}{N_{transmitted}} \tag{42}$$

Where $N_{acknowledged}$ represents the number of acknowledged packets and $N_{transmitted}$ is the total number of transmitted packets.

Drones employ error detection and correction mechanisms to identify and mitigate transmission errors during data transmission. Error detection codes, such as Cyclic Redundancy Check (CRC), enable receivers to detect corrupted packets, while error correction codes, such as Hamming codes, facilitate error recovery. Equation (43) is applied to check errors.

$$P_{error} = \frac{N_{corrupted}}{N_{received}} \tag{43}$$

Where $N_{corrupted}$ represents the number of corrupted packets detected and $N_{received}$ is the total number of received packets.

In cases where data packets cannot be successfully delivered, receivers send Negative Acknowledgements (NACKs) to request retransmissions. The NACK rate (R_{NACK}) indicates the frequency of unsuccessful data transmissions relative to the total transmitted packets. Equation (44) is applied to compute R_{NACK}.

$$R_{NACK} = \frac{N_{NACK}}{N_{transmitted}} \tag{44}$$

Where N_{NACK} represents the number of NACK packets received.

Drones initiate retransmissions of the affected data packets upon receiving a NACK or experiencing acknowledgement timeout. The retransmission timeout ($T_{retransmit}$) calculated using Equation (45) determines the maximum duration a drone waits before retransmitting the packet.

$$T_{retransmit}(n) = Random(T_{min}(n), T_{max}(n)) \tag{45}$$

Where $Random(T_{min}(n), T_{max}(n))$ generates a random value within the specified time limit.

The Automatic Repeat reQuest (ARQ) mechanism enables drones to automatically retransmit data packets upon detecting transmission errors or unsuccessful acknowledgements. Go-Back-N ARQ manages the retransmission process based on received acknowledgements and NACKs. Equation (46) is applied to calculate $P_{retransmit}$.

$$Overall\ P_{retransmit} = \prod \frac{N_{retransmissions}}{N_{total\_packets}} \tag{46}$$

Where $N_{retransmissions}$ represents the number of packet retransmissions triggered by the ARQ mechanism and $N_{total\_packets}$ is the total number of transmitted packets.

3.9. Return to Surface

The Return to Surface phase in KRP mirrors the ascent of a kingfisher back to the surface after a successful dive. In KRP, this phase involves collecting feedback from network operations and optimizing routing strategies based on observed performance metrics. It encompasses mathematical formulations and procedures for feedback collection, analysis, and routing optimization. Drones collect performance metrics such as packet delivery ratio, end-to-end delay, and throughput to evaluate the effectiveness of routing strategies and network operations. Performance metric collection involves periodically measuring and recording relevant metrics during network operation where Equation (47) is fully applied.

$$P_{metric} = \frac{N_{successful\_packets}}{N_{total\_packets}} \tag{47}$$

Where $N_{successful\_packets}$ represents the number of successfully delivered packets and $N_{total\_packets}$ is the total number of transmitted packets.

After collecting performance metrics, drones analyze the feedback to identify trends, patterns, and areas for improvement in network performance. Equation (48) indicates the feedback analysis involving statistical analysis, trend detection, and anomaly detection techniques to extract meaningful insights from collected data.

$$F_{analysis} = Analyze(P_{metric}) \tag{48}$$

Based on the results of the feedback analysis, drones select route optimization strategies to improve network performance and address identified issues. Equation (49) provides route optimization strategies, including route recalibration, adaptive routing parameter adjustment, or route reconfiguration based on observed network dynamics.

$$S_{optimization} = Select\_Strategy\left(F_{analysis}\right) \tag{49}$$

In dynamic and uncertain environments, reinforcement learning techniques may be employed by drones to adaptively optimize routing decisions adaptively, conditioned on observed outcomes and received environmental feedback. Apply reinforcement learning algorithms, namely Deep Q-Network (DQN) in KRP. It learns optimal routing policies through trial-error interactions with the network environment.

$$Q(s,a) = Q(s,a) + \alpha \times [R(s,a) + \gamma \times maxQ(s',a') - Q(s,a)] \tag{50}$$

Where $Q(s,a)$ represents the quality of taking action a in state $s, R(s,a)$ denotes the immediate reward obtained from taking action a in state s, α is the learning rate, γ is the discount factor, s' is the next state, and a' is the following action.

Drones change routing parameters dynamically to adapt to changing network conditions and requirements, including route weights, transmission power levels and packet prioritization policies. Dynamic parameter adjustment mechanisms described by Equation (51) monitor the network performance dynamically and adjust routing parameters continuously.

$$P_{adjust} = \frac{\Delta Parameters}{\Delta t} \tag{51}$$

Where $\Delta Parameters$ represents the change in routing parameter value, and Δt is the time interval over which the adjustment occurs.

In addition to route optimization, drones may use cross-layer optimization techniques that leverage information from multiple protocol layers to improve overall network performance. Cross-layer optimization enables drones to jointly optimize routing, Medium Access Control (MAC), and physical layer parameters to enhance efficiency and throughput. Equation (52) plays a crucial role in optimizing the cross-layers.

$$O_{cross-layer} = \sum_{i=1}^{n} W_i \times M_i \tag{52}$$

Where W_i represents the weight assigned to the metric M_i from the i^{th}protocol layer and n is the total number of protocol layers considered.

3.10. Prey Handling

The Prey Handling phase in the KRP symbolizes a kingfisher's successful delivery of prey to its destination. In KRP, this phase corresponds to the reliable delivery of data packets to their intended destinations. Upon receiving data packets, drones identify the destination nodes based on destination addresses or routing table lookups. Equation (53) is applied to determine the destination and ensure that data packets are delivered to the correct recipients.

$$D_{destination} = Lookup\_Destination\left(D_{packet}\right) \tag{53}$$

Where D_{packet} represents the destination address of the data packet.

The end-to-end delay ($T_{end-to-end}$) measures the time data packets travel from the source node to the destination node. It includes transmission delay, propagation delay, queuing delay, and processing delay along the route.

$$T_{end-to-end} = T_{arrival} - T_{departure} \tag{54}$$

Where $T_{arrival}$ is the time when the packet arrives at the destination, and $T_{departure}$ is the time when the packet was sent from the source.

The packet delivery ratio $\left(R_{delivery}\right)$ specified in Equation (55) quantifies the proportion of successfully delivered packets relative to the total transmitted packets. It reflects the effectiveness of data delivery within the network.

$$R_{delivery} = \frac{N_{delivered}}{N_{transmitted}} \tag{55}$$

Where $N_{delivered}$ represents the number of packets successfully delivered to the destination and $N_{transmitted}$ is the total number of transmitted packets.

Drones use congestion control mechanisms to regulate the packet rate transmission to prevent congestion and maintain smooth data delivery and network overload. Transmission rates adjust based on observed network conditions dynamically in congruency control algorithms. Equation (56) examines whether there is congestion and performs suitable actions.

$$P_{control} = \begin{cases} 1 & if\ congestion \\ 0 & otherwise \end{cases} \tag{56}$$

For scenarios where Quality of Service (QoS) needs are specified, drones ensure QoS properties to promise delivery of data packets with prefixed quality parameters (e.g., minimum delay, maximum jitter, or guaranteed bandwidth). QoS enforcement mechanisms use QoS requirements to prioritize packets and allocate the network resources accordingly. The QoS is checked using Equation (57).

$$P_{QoS} = \begin{cases} 1 & if\ QoS\ requirements\ met \\ 0 & otherwise \end{cases} \tag{57}$$

After successfully delivering data packets to their destinations, drones send Acknowledgements (ACKs) to the source node to confirm delivery. Equation (58) is applied to check the acknowledgement where the successful delivery ensures that the source node receives feedback on the status of transmitted packets.

$$P_{acknowledgment} = \begin{cases} 1 & if\ successful\ delivery\ acknowledged \\ 0 & otherwise \end{cases} \tag{58}$$

3.11. Framework of KRP

The KRP framework provides a comprehensive algorithm and flow diagram for efficient drone communication routes. Figure 1, "Framework of KRP," illustrates the overall process, integrating phases such as route discovery, path establishment, and data transmission. Algorithm 1 details the working process, outlining the procedural steps and decision-making mechanisms. This framework ensures dynamic adaptation to network conditions and optimized resource utilization within DANET.

Algorithm 1: KRP

Input:
- Network topology information
- Data packets to be transmitted
- Routing parameters
- Quality of Service (QoS) requirements
- Feedback from network operations

Output:
- Successfully delivered data packets
- Feedback for route optimization

Procedure:
1. Initialize routing tables and set up initial route configurations and QoS parameters.
2. Exchange control packets to discover neighboring nodes and establish communication links.
3. Perform route discovery using proximity, link quality, and resource availability metrics.
4. Evaluate and select the most suitable route based on route metrics and QoS constraints.
5. Establish the selected route by configuring necessary parameters and setting up communication paths.
6. Generate and transmit data packets along the established route.
7. Relay and forward data packets to ensure reliable delivery.
8. Wait for acknowledgements and handle transmission errors with retransmissions or error correction.
9. Collect and analyze feedback from network operations, then adjust routing parameters and optimization strategies.
10. Identify destination nodes, calculate end-to-end delay and packet delivery ratio, and send acknowledgements for successfully delivered packets.

3.12. Advantages of KRP

- Ensures reliable data transmission by dynamically prioritizing routes based on key metrics like latency, bandwidth, and packet delivery requirements.
- Maintains longer-lasting communication links through adaptive routing that minimizes disruptions caused by network topology changes.
- Enhances the packet delivery ratio by selecting efficient and stable routes, minimizing losses, and improving data reliability even under challenging conditions.
- Supports increasing numbers of drones without compromising network performance, making it suitable for large-scale deployments in hazardous scenarios.
- Ensures faster data transmission by reducing unnecessary control messages and rapidly converging to stable routing structures.
- Detects and resolves link failures swiftly, enabling continuous communication and reducing downtime in dynamic and unpredictable environments.

4. Results and Discussion

4.1. Simulation Setting

The DANET is simulated using the NS-3 simulation tool in this study on ad hoc networks. The simulations last for 900 seconds, with data being recorded at one second intervals and alongside the random seeds. Network parameters include nodes between 50 and 500 in a 1000m x 1000m area using grid and random connectivity with the Random Waypoint mobility model. Examples of IEEE 802.11 communication standards are used. There are other external factors like wind speed and any obstacles that may be on the way. Table 2 gives the simulation settings.

4.2. Packet Delivery Ratio and Packet Loss Ratio Analysis

Figure 2 showcases the comparative analysis of Packet Delivery Ratio (PDR), and Figure 3 highlights Packet Loss Ratio (PLR) among three routing protocols, AODV, QSCR, and KRP, across various drone counts. Figure 4 and Figure 5 provide the average PDR and PLR. PDR and PLR evaluate the efficiency and reliability of packet delivery within the network.

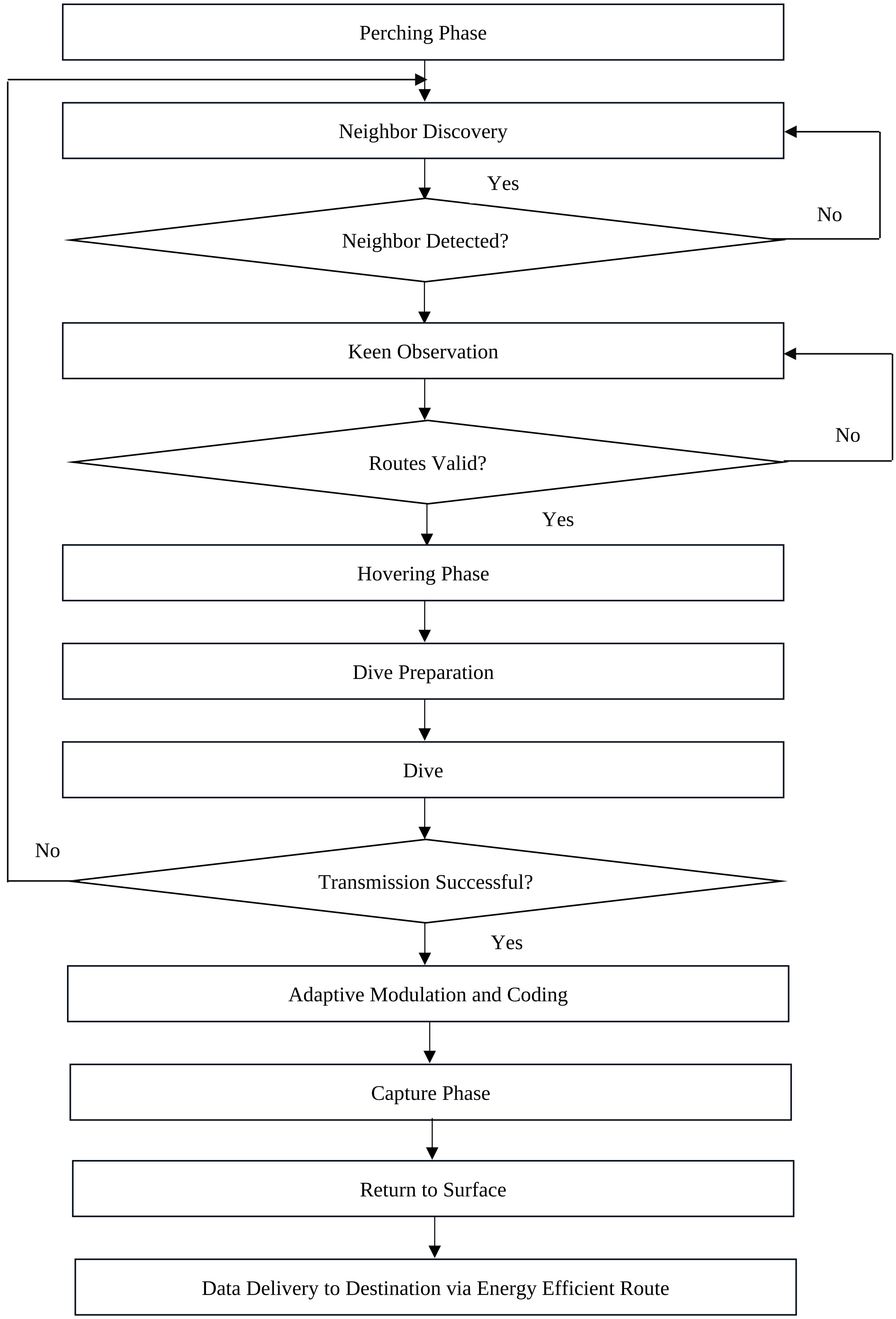

Fig. 1 Framework of KRP

Table 2. Simulation setting

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
Communication Parameters	MAC and PHY Layers	IEEE 802.11
	Transmission Range	80m - 240m
	Channel Bandwidth	20 MHz
	Propagation Model	Two-Ray Ground Reflection
	Path Loss Model	Free Space, Two-Ray Ground
	Collision Avoidance	RTS/CTS
Traffic and Protocol Parameters	Protocol	AODV, DSR, OLSR,..
	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
	Sleep Mode Energy Consumption	0.1 Joules/second
	Packet Transmission Energy	0.5 Joules/packet
	Packet Reception Energy	0.3 Joules/packet

Table 3 and Table 4 provides the simulation results with its average. AODV protocol significantly demonstrates a lower PDR and a higher PLR as drones increase. Vulnerability to attacks like blackhole and wormholes significantly impacts the PDR, reducing it to 21.541% for 500 drones and increasing the PLR to 78.459%. Such attacks disrupt the routing process, causing packet losses and reduced network reliability.

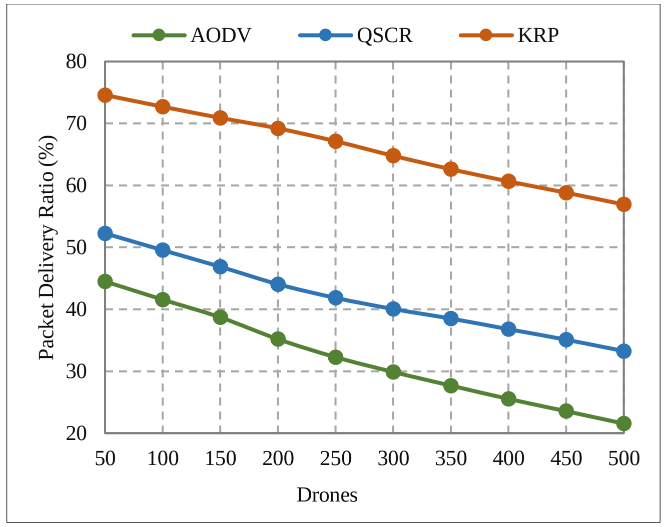

Fig. 2 Packet delivery ratio

Table 3. Packet delivery ratio

No. of Drones	AODV	QSCR	KRP
50	44.492	52.260	74.587
100	41.557	49.538	72.699
150	38.696	46.866	70.901
200	35.178	44.049	69.207
250	32.268	41.841	67.129
300	29.881	40.044	64.783
350	27.680	38.501	62.617
400	25.530	36.788	60.650
450	23.549	35.088	58.819
500	21.541	33.251	56.921
Average	32.037	41.823	65.831

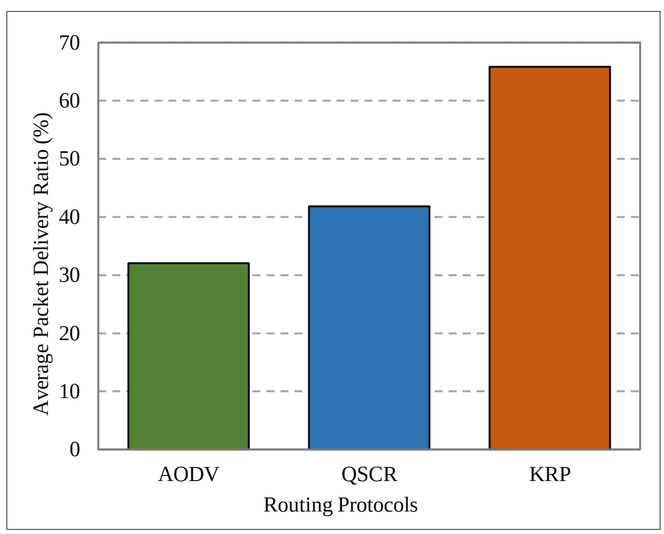

Fig. 3 Average packet delivery ratio

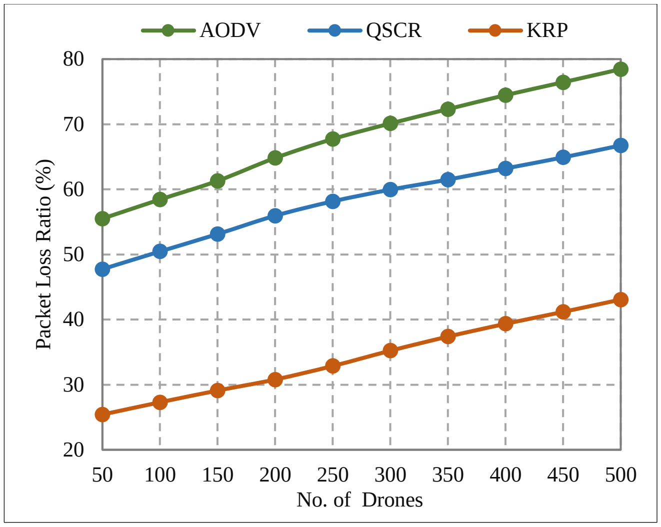

Fig. 4 Packet loss ratio

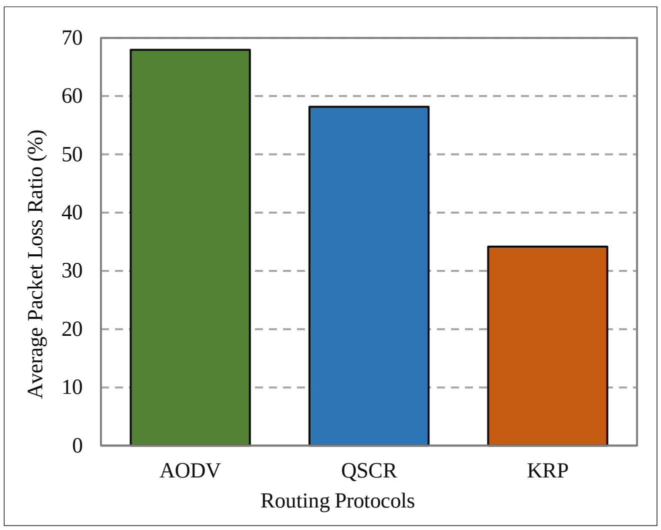

Fig. 5 Average packet loss ratio

Table 4. Packet loss ratio

No. of Drones	AODV	QSCR	KRP
50	55.508	47.740	25.413
100	58.443	50.462	27.301
150	61.304	53.134	29.099
200	64.822	55.951	30.793
250	67.732	58.159	32.871
300	70.119	59.956	35.217
350	72.320	61.499	37.383
400	74.470	63.212	39.350
450	76.451	64.912	41.181
500	78.459	66.749	43.079
Average	67.963	58.177	34.169

KRP protocol shows substantial improvement in PDR, achieving an average of 65.831% across all drone counts. Like a kingfisher's targeted diving, its highly precise data delivery mechanism minimizes the likelihood of packet interception or loss. This precision results in a lower PLR, averaging 34.169%, enhancing overall network performance and reliability compared to AODV and QSCR. The optimized routing in KRP ensures efficient data transmission and robust network communication. KRP's adaptive routing mechanism swiftly adjusts to network changes, stabilizing performance in dynamic environments.

4.3. Latency Analysis

Figure 6 illustrates latency comparisons for AODV, QSCR, and KRP protocols across various drone counts. Latency measures the time a packet takes to travel from the source to the destination, indicating network responsiveness.

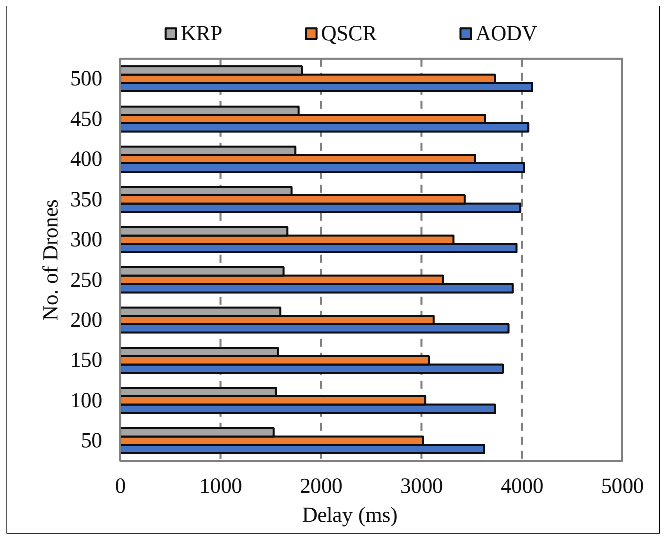

Fig. 6 Latency analysis results

AODV protocol exhibits high latency values. This protocol incurs significant delays, particularly in dynamic environments with many drones. The need for frequent route discoveries and updates causes substantial network congestion. With 500 drones, AODV records a latency of 4105 milliseconds, indicating substantial inefficiencies. The protocol's susceptibility to network attacks also exacerbates delays, as compromised routes require reestablishment, further increasing latency. QSCR protocol demonstrates moderate latency values.

Frequent control message exchanges for managing clusters and updating learning models lead to increased network traffic, resulting in higher latency. With 500 drones, the latency is recorded at 3732 milliseconds. Increased network traffic causes congestion, leading to delays and reduced efficiency. Challenges handling node failures and synchronization further contribute to this latency, impacting overall network performance.

Table 5. Latency analysis result values

No. of Drones	AODV	QSCR	KRP
50	3623	3017	1526
100	3735	3039	1549
150	3808	3073	1570
200	3868	3120	1593
250	3909	3214	1626
300	3948	3320	1664
350	3984	3431	1707
400	4023	3537	1744
450	4066	3633	1778
500	4105	3732	1810
Average	3907	3312	1657

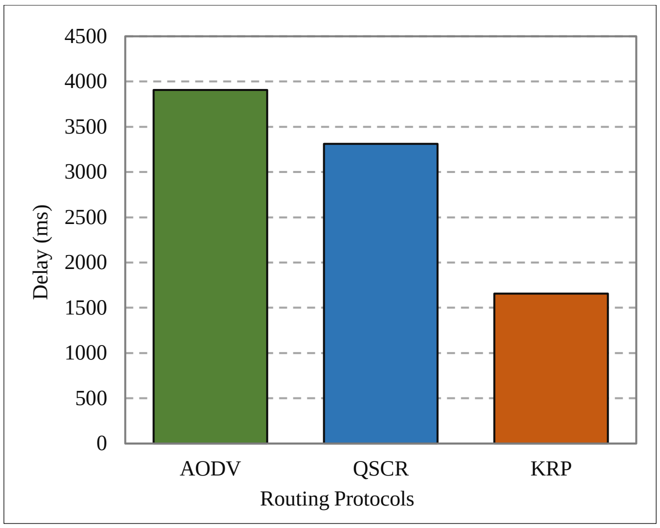

Fig. 7 Average latency

KRP protocol shows significantly lower latency, averaging 1657 milliseconds across all drone counts. Precision in data delivery minimizes unnecessary control messages and optimizes route selection, reducing network congestion and speeding up data transmission. Rapid convergence to a stable routing structure ensures quick establishment and maintenance of routes, further reducing latency. The streamlined, targeted routing mechanism of KRP ensures swift and reliable data packet delivery, enhancing overall network performance and responsiveness compared to AODV and QSCR. This results in a more efficient and robust communication network, particularly in dynamic environments with many drones. Table 5 provides the simulation results obtained for the metric Latency. Figure 7 provides a comparison of average latency.

4.4. Energy Consumption Analysis

Figure 8 presents the comparative analysis of energy consumption for AODV, QSCR, and KRP protocols across various drone counts, as shown in Table 6. Energy consumption is a critical metric for evaluating the efficiency of routing protocols, particularly in resource-constrained environments.

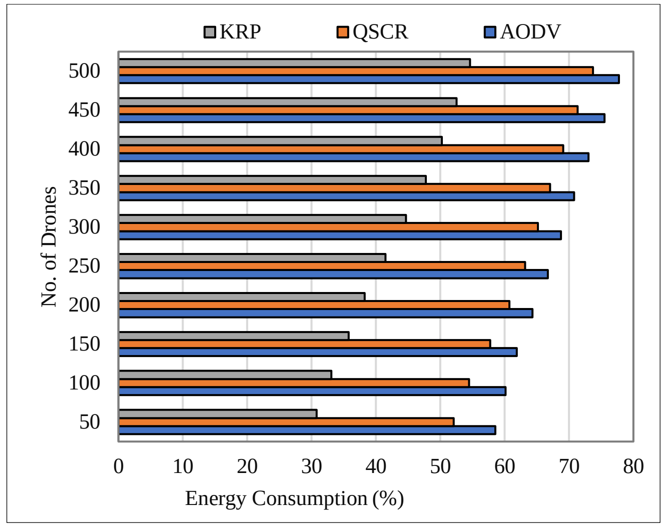

Fig. 8 Energy consumption analysis results

AODV protocol exhibits high energy consumption values. Frequent route discoveries and maintenance activities lead to significant energy expenditure. With 500 drones, AODV records an energy consumption of 77.762%, reflecting substantial inefficiencies. Nodes involved in multiple route discoveries and updates deplete their batteries quickly, resulting in non-uniform battery usage and reducing the overall network lifespan. QSCR protocol shows moderate energy consumption values. The frequent exchange of control messages to manage clusters and update learning models increases energy usage. With 500 drones, QSCR's energy consumption stands at 73.713%. Synchronization challenges and handling node failures further contribute to higher energy consumption, impacting network sustainability.

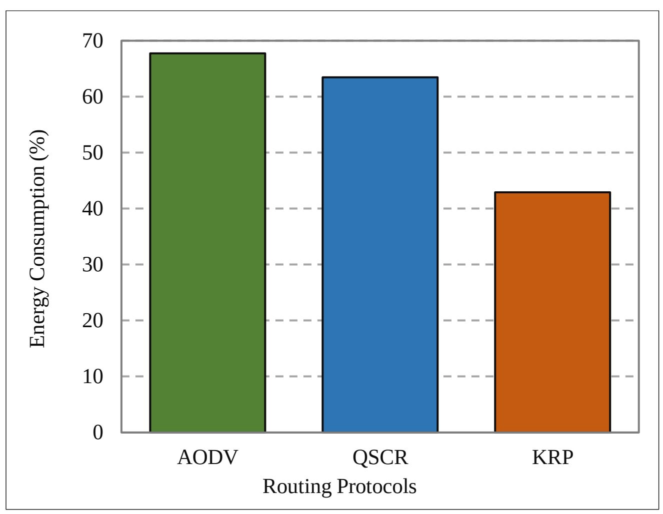

Fig. 9 Average energy consumption

KRP protocol demonstrates lower energy consumption, averaging 42.915% across all drone counts. The protocol's precision in data delivery minimizes unnecessary control messages and optimizes routing efficiency.

Table 6. Energy consumption result values

No. of Drones	AODV	QSCR	KRP
50	58.567	52.093	30.800
100	60.135	54.494	33.070
150	61.905	57.741	35.749
200	64.326	60.192	38.260
250	66.685	63.192	41.485
300	68.725	65.149	44.648
350	70.764	67.065	47.730
400	73.043	69.089	50.265
450	75.521	71.342	52.551
500	77.762	73.713	54.596
Average	67.743	63.464	42.915

By reducing the need for frequent route discoveries and updates, KRP conserves energy. This efficient energy usage extends the network's operational life, ensuring sustainable performance in dynamic environments. The streamlined, targeted routing mechanism of KRP enhances overall network efficiency, making it a robust choice compared to AODV and QSCR. Figure 9 provides the average energy consumption.

4.5. Link Stability

Link stability measures how long a communication link remains active without interruption. Figure 10 shows the analysis of link stability for AODV, QSCR, and KRP protocols with different numbers of drones, as presented in Table 7. Figure 11 provides the results of average link stability of routing protocols in hazardous DANET.

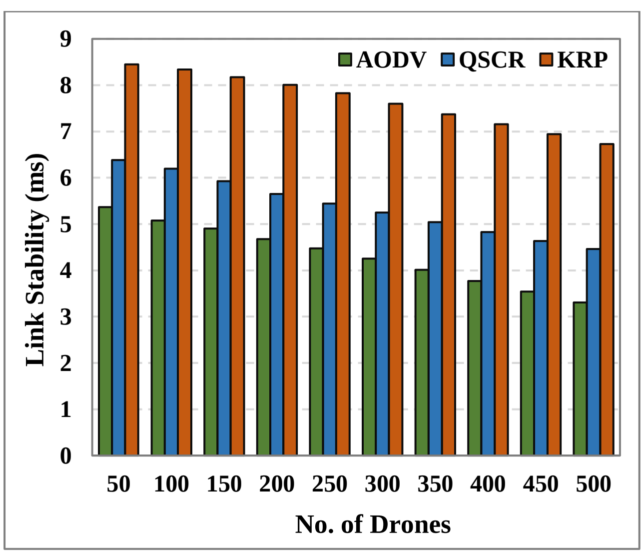

Fig. 10 Link stability analysis results

AODV exhibits lower link stability values, with frequent route discoveries leading to unstable links. At 500 drones, AODV records an average link stability of 3.310 milliseconds. The dynamic nature of AODV, with its frequent need for route maintenance, results in shorter stable link durations, causing disruptions in communication. QSCR has moderate link stability. The control message exchanges for cluster management and learning model updates impact stability. With 500 drones, QSCR achieves a link stability of 4.458 milliseconds. Challenges in synchronization and managing node failures contribute to the moderate stability observed.

Table 7. Link stability result values

No. of Drones	AODV	QSCR	KRP
50	5.368	6.380	8.449
100	5.076	6.197	8.342
150	4.905	5.929	8.175
200	4.677	5.652	8.006
250	4.474	5.443	7.825
300	4.254	5.246	7.597
350	4.011	5.045	7.371
400	3.771	4.829	7.158
450	3.545	4.632	6.942
500	3.310	4.458	6.731
Average	4.339	5.381	7.660

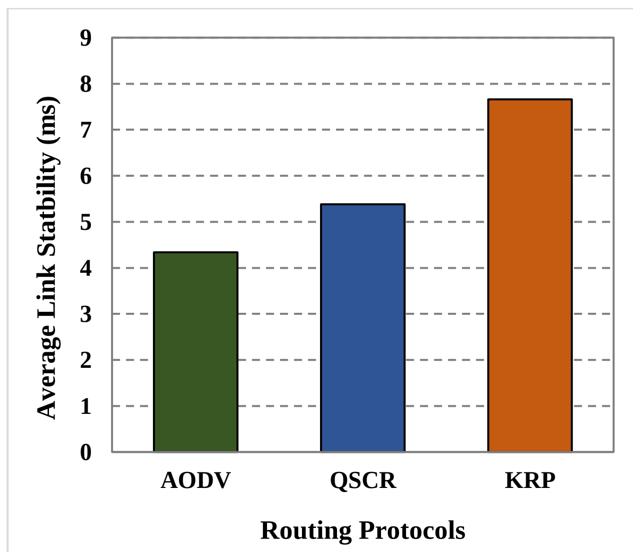

Fig. 11 Average link stability

KRP shows significantly higher link stability, averaging 7.660 milliseconds across all drone counts. The protocol's precise data delivery and efficient routing mechanisms lead to longer stable link durations. By reducing unnecessary control messages and optimizing route paths, KRP maintains more consistent and reliable links. This improvement in link stability enhances network performance, ensuring continuous and robust communication. The ability to adapt swiftly to environmental changes and maintain stable links makes KRP an excellent choice for dynamic networks with a high number of drones.

4.6. Hop Count Analysis

The hop count metric represents the number of intermediate nodes a packet traverses from the source to the destination. Figure 12 displays the hop count analysis for AODV, QSCR, and KRP protocols across different numbers of drones, as detailed in Table 8. Figure 13 provides the Average Hop Count routing protocol in hazardous DANET.

AODV exhibits consistently high hop counts, with an average of 10.059 hops. The need for frequent route discoveries and updates in dynamic environments contributes to longer paths, increasing the number of hops. This higher hop count leads to delays in packet delivery and higher network overhead, reducing overall efficiency. QSCR shows a moderate hop count, averaging 9.031 hops. While clustering and learning models help to some extent, the frequent control message exchanges and the need to manage synchronization and node failures still result in many intermediate nodes. This moderate hop count indicates that QSCR is more efficient than AODV but still has room for improvement.

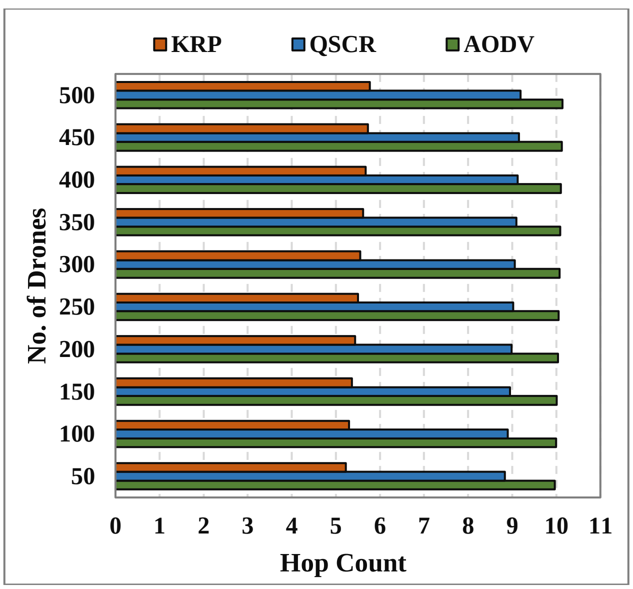

Fig. 12 Hop count results

KRP makes a difference with a rather low hop count of 5.516 average hops. Optimized routing protocols and precise data transport result in minimal intermediate nodes of the system. This comprises a lower hop count, meaning KRP effectively sets up packet transmission through the shortest and direct routes. In this context of operation, KRP improves the data and signaling transmission rate and the network integration efficiency by reducing unnecessary jumps. This improvement makes KRP a much more practical mechanism for achieving and sustaining low hop counts for the purpose of fast and highly reliable inter-drone communication.

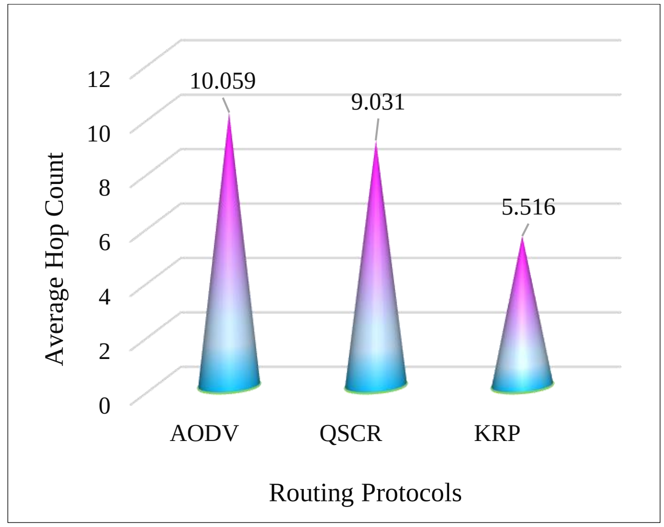

Fig. 13 Average hop count

Table 8. Hop count analysis result values

No. of Drones	AODV	QSCR	KRP
50	9.969	8.834	5.225
100	9.992	8.896	5.301
150	10.010	8.946	5.360
200	10.035	8.988	5.436
250	10.055	9.025	5.499
300	10.072	9.059	5.553
350	10.090	9.091	5.614
400	10.107	9.123	5.672
450	10.124	9.156	5.726
500	10.141	9.188	5.773
Average	10.059	9.031	5.516

5. Conclusion

This paper evaluates the Kingfisher Routing Protocol as a suitable solution to address the major issues of Drone Ad Hoc Networks (DANET) in danger zones. These environments demand perpetual coverage, consistent communication, and low energy consumption, which can hardly be maintained because of the fluid topologies of drone networks.

To deal with these issues, KRP utilizes the algorithm for dynamic routing based on the current network conditions to provide proper and steady communication and reduce energy expenditure. Arrangement of network density, signal strength, and route selection at the KRP improves the quality of service through the designated quality of service. Other assessment outcomes of the simulation studies show that KRP boosts up the packet delivery, decreases the latency as well as enhances energy consumption and link stability remarkably. The outcome of these measures reconfirms the KRP's ability to increase the practical readiness of DANET in severe conditions and is effective for communication preservation in extreme situations. There could be future improvements to make use of machine learning to make the adaptation process of KRP more intelligent and come up with predictive routing adjustments from the data collected predisposing and changes in the network. Furthermore, introducing the KRP to multi-drone cooperative missions and reviewing its efficacy in various environmental conditions may improve the broad applicability of KRP in various operation types.

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