

Design and Implementation of A Bio-Inspired Optimization-Based Reactive Routing Protocol for Collision-Aware Routing in Fanets

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Abstract - The fast adoption of UAVs in Flying Ad-Hoc Network (FANETs) has made it possible to have a wide range of applications, such as surveillance, disaster response, precision agriculture, and environmental monitoring. Nevertheless, the decentralized and three-dimensional nature of FANETs pose significant challenges especially when it comes to the provision of reliable communication and safe navigation. Mid-air collisions are a major threat that directly affects the performance of the missions and the durability of UAVs. Conventional routing schemes, which are mostly ground-based or static aerial routing schemes, are not usually suitable to the highly dynamic mobility and the high rate of topology changes of FANETs. The paper presents a BI-CAR which integrates swarm intelligence in reactive routing to attain collision-aware communication. The protocol uses distributed decision-making and adaptive mobility awareness in minimizing the probability of collisions and maximizing routing efficiency, and is grounded in biological principles, like insect swarms and bird flocks. BI-CAR is a dynamic route selection algorithm that considers environmental factors, UAV mobility, and collision metrics. The outcomes of simulation in the conditions of representative FANETs demonstrate that BI-CAR can attain reduced collision rate, enhanced route stability, and enhanced ratio of packet delivery in contrast to the current protocols. The results show that bio-inspired methods may be used to fulfill the safety and adaptability needs of FANETs to enable them to be deployed to complex and dynamic environments.

Index Terms : FANET, UAV, Routing Protocols, Collision-Aware Routing, Bio-Inspired Algorithms. Swarm Intelligence.

1. INTRODUCTION

UAVs are finding application in mission-critical applications, including precision agriculture, environmental surveillance, military surveillance, and disaster management. Their mobility and versatility have enhanced the development of FANETs that employ UAVs to create dynamic and self-organising wireless communication systems in the air. As opposed to traditional Mobile Ad-Hoc Networks (MANETs) and Vehicular Ad-Hoc Networks (VANETs), FANETs exist in a highly dynamic three-dimensional space where node density, velocity and altitude are in a state of perpetual flux. These properties pose significant routing and coordination and safety challenges that are much more complicated than those found in terrestrial networks [1].

Collision avoidance is one of the main issues of FANET functions. UAVs (either single or swarm) should be able to work in a congested and unpredictable airspace and maintain a stable communication connection. Collision in the air does not only lead to the loss of the expensive aerial platforms but also poses the risk of corrupting data, disrupting missions and even causing damage to property or human beings. The routing solutions currently available, most of which are variations on MANET-based solutions, do not offer the responsiveness and spatial awareness required in real-time collision-aware routing in such volatile and safety-critical situations [2].

Bio-inspired optimization strategies have become the potential solutions to address these constraints to provide complex and adaptive networking environments. Scalability, decentralization and efficiency can be found in nature in the form of biological systems like bird flocks, fish schools and insect swarms, especially in the domain of collective navigation and collision avoidance.

Such behaviors as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) are modeled using algorithms that provide a useful basis in designing dynamic routing strategies that can adjust to changes in topology and maintain network reliability [3][4].

This paper is encouraged by these observations, and thus, it presents the BI-CAR, a new strategy that is specific to collision-aware communication in FANETs. BI-CAR allows UAVs to find safe and efficient routes dynamically with no central control and assess the collision risk in real-time by integrating environmental conditions, node mobility, and collision probability with geographical awareness. The protocol improves the geographical awareness and network resilience through the combination of the environmental factors, node mobility and collision probability measures. Ample simulations have been performed with realistic FANET conditions to test the performance of BI-CAR. Findings indicate that the BI-CAR is always superior to the current routing schemes in terms of minimizing the rate of collisions, enhancing the stability of routes, and having a high ratio of packet delivery. The results highlight the opportunities of bio-inspired optimization as a platform to build adaptive and safety-conscious routing schemes in UAV networks, and thus enable the safe and reliable use of FANETs in complex operation scenarios [5][6][7].

1.1. Problem Statement

FANETs facilitate the dynamic, self-organizing communication systems between groups of UAVs to be used in surveillance, disaster management, agriculture and environmental monitoring. In spite of their potential, FANETs are subject to severe problems because the density of the nodes, their velocity and their altitude in a three-dimensional environment change frequently. The outcomes of these dynamics are unstable topologies, inconsistent patterns of communication, and augmented safety problems. Mid-air collision is one of the most urgent problems that may lead to the failure of the mission, loss of data, and destruction of UAV systems. The current routing protocols are based on the modifications of MANETs and VANETs, which do not aim to handle high mobility and collision risks of UAV swarms. As a result, they are not responsive and situational awareness in such settings. In order to address this shortcoming, CAR protocols that dynamically adapt to the conditions in FANETs and are safe and reliable in communication are required.

1.2. Motivation

In FANETs, the growing utilisation of UAVs is advancing their use of UAVs in disaster management, precision agriculture, environmental monitoring, and infrastructure inspection. The major benefits of FANETs are that they can be deployed quickly and with wide coverage; however, operating in dynamic three-dimensional airspace poses significant safety hazards, especially during mid-air collisions. Current routing protocols most of which are based on terrestrial networks do not provide the real-time flexibility and knowledge required in such a situation. A good solution is offered by bio-inspired optimization because natural systems are efficient, decentralized, and adaptive with regard to collision avoidance. The necessity to create the Collision-Aware Routing protocol that enhances safety and reliability of communication and to provide the opportunity to employ FANETs successfully in the complex missions is the driving force of this research.

1.3. Objective

The primary aim of the research is the creation and implementation of a bio-inspired optimization-based reactive routing protocol of Collision Aware Routing (CAR) in FANETs. The protocol suggested is based on addressing the challenges of operating in the dynamic three-dimensional airspaces, on the example of biological systems, which naturally demonstrate effective collision-avoidance mechanisms. To this effect, the paper will develop a prototype of an optimization model that relies on collective behaviours in flocks of birds and schools of fish so as to enable UAVs to make decentralized and adaptive routing choices. The protocol is created keeping in mind the flexibility in real-time, it encompasses the evaluation of the risks of collision, it is based on the UAV mobility patterns and the environmental factors. It will be simulated and where practicable experimented in the real world and its performance compared by collision avoidance, routing efficiency and the use of energy against existing schemes. Based on the empirical data, the protocol will be streamlined and improved to make it more reliable and responsive. Through these objectives, the study ultimately aims at the enhancement of the security and effectiveness of UAVs that will facilitate the broader and more secure application of FANETs to mission-critical operations.

1.4. Organization

The paper is organised as follows: Section 2 presents a review of related research on FANET routing and collision avoidance, outlining key developments and gaps. The conceptual framework and design principles of the proposed BI-CAR protocol are found in section 3. The routing mechanism and the algorithmic workflow are detailed in Section 4. Section 5 gives the implementation strategy and simulation environment that will be used in evaluation. Discussed in section 6 is the performance

measures and evaluation process. In section 7, the results and comparative discussion of the effectiveness of BI-CAR are provided. Finally, Section 8 provides a conclusion of the paper and outlines potential future research and future validation.

2. LITERATURE REVIEW

The design of routing protocols of the FANETs has been receiving an increasing attention since UAVs have become popular in the sphere of surveillance, disaster response, environmental monitoring, and aerial delivery services. Unlike the terrestrial networks, FANETs are very dynamic in three dimensional environment whereby network topology changes on a regular and unpredictable basis. The absence of infrastructure and other issues such as bandwidth, energy, fluctuating altitudes and the necessity to transfer information in real-time makes it significantly more complex to guarantee that communication between UAVs is sound in contrast with the conventional networks [8].

Early research attempted to generalize routing algorithms of MANETs and VANETs like Ad hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR) and Optimized Link State Routing (OLSR). These protocols are efficient in ground-based environments, but they experience issues with the aerial environment. They do not perform well in high-mobility and lack the spatial and directional capability to support UAV navigation within the three-dimensional airspace. These limitations highlight the necessity of FANET-specific routing techniques that involve mobility forecasting, GPS-based place tracking, dynamic assessment of link quality, and adaptive path maintenance to achieve resilient and effective communication [9].

2.2. Reactive and Proactive Routing in FANETs

The characteristics that make routing in FANETs extremely challenging include high mobility of nodes, topology that is constantly changing as well as intermittent connection. Traditional proactive routing, such as OLSR and DSDV are routing protocols where routing tables are updated by exchanging them on a regular schedule. In spite of this approach giving real time route availability and topology awareness, it generates significant control overhead. The majority of this information in the extremely dynamic FANET settings becomes outdated in a short time and this wastes precious bandwidth and efficiency.

Reactive protocols like AODV and DSR are more adaptable to FANETs because they reduce the quantity of control traffic that makes them more adaptable to dynamic conditions. Topological changes, sensitivity to topological changes, and absence of proactive collision avoidance schemes are the current limitations. To a great extent, they are the ones that set connection-based communication paths without taking into account airspace congestion, UAV paths, or collision probability in the airspace.

The nature of requirements of FANET does not include proactive and reactive protocols because it is not conventional. Mobility prediction, environmental awareness and collision-avoidance strategies are significant to routing. There is a higher potential of integrating geographic data, cross-layer optimization and flight-path coordination in providing reliable, safe and efficient communication in aerial networks [10].

2.3. Geographic and Position-Based Routing

Greedy Perimeter Stateless Routing (GPSR), forwards UAVs positioned packets to maintain the complex routing tables. It functions poorly in highly dynamic networks; however, it performs well in networks with minimal mobility or stability. Their functioning ability deteriorates in extremely dynamic settings like FANETs, while being effective in relatively static or low-mobility scenarios. This is due to the outdated location information [11].

Trajectory prediction and Location-Aided Routing (LAR) are the two methods that have been proposed to address these challenges. The reason why trajectory prediction work is so is because it predicts the routing decisions based on the future positions of the UAVs and LAR limits the route finding operations based on a given search area. Though these methods do work, these methods do not consider some important aspects like UAV speed, direction of flight, changes in altitude, and proximity with other objects. Thus, they cannot sustain collision dynamics in rapidly changing airspaces.

Some of the methods that have been proposed to overcome these challenges include Trajectory prediction and Location-Aided Routing (LAR). The superior routing decisions are made with the help of trajectory prediction, and LAR limits the search space. However, they are not much concerned with such crucial parameters as the speed of UAVs, their direction, and changes in elevation, and the obstacles that can be encountered in the vicinity [12].

An obvious need for routing strategies is collision-awareness and context-sensitivity of FANET topologies, which combine mobility prediction and environmental awareness. These specific laws must safeguard the UAV activities in hazardous air environments.

2.4. Swarm Intelligence and Bio-Inspired Approaches

A huge potential has been well articulated by bio-inspired optimization algorithms in solving complex decision making problems particularly in dynamic and uncertain conditions. The ACO, PSO, and ABC methods are inspired by natural foraging by ants, swarming by flocks of birds and swarming by bees. Such strategies affect the processes of decentralization, flexibility, and resilience to offer effective solutions to extremely changing conditions [13][14].

Bio-inspired techniques are more appropriate to FANETs, where UAVs work in rapidly changing topologies that have intermittent connectivity and limited resources. An example is that PSO has been applied to improve conventional protocols such as AODV that can optimize multi-objective over parameters such as reliability, energy consumption, and hop count [15].

To these developments, the latest bio-inspired solutions do not ignore collision avoidance, which is a very important feature in FANETs due to high velocity of UAV and space constraints. The latest approaches Quality of Service (QoS) parameters overlooked the spatial distance and route prediction. In a case, PSO-based routing can be efficient in terms of the paths but lacks collision detection or mitigation systems [16].

The next generation study should involve the spatiotemporal awareness, trajectory prediction, and collision risk determination to attain not only the efficiency of the communication, but also the safety of the flight. This growth is required to offer scalable, secure, and reliable operations in the congested three-dimensional UAV cases.

2.5. Collision Avoidance in FANETs

Reactive maneuvers, centralized flight control systems or onboard sensing techniques does not rely on the routing process. Nevertheless, routing protocols that integrate collision avoidance mechanisms have not received a lot of research. This discontinuity separates the physical-layer safety and network-layer decision-making in distributed and autonomous UAV swarms and poses a major challenge [17].

To fill this gap, this paper suggests a novel bio-inspired reactive routing algorithm that incorporates communication and safety aspects. The protocol combines real-time awareness with swarm intelligence concepts to improve routing efficiency and collision avoidance. It also incorporates collision risk assessment into route discovery and maintenance, unlike traditional methods, where the UAVs adjust the changing topologies and ensure the safe separation, as well as the maintenance of strong connectivity. These proposed techniques are consistent with network-layer routing along with physical-layer safety and more resilient and mission-ready deployments of FANETs [18].

2.6. Technological Gap

Table 1 explains the advantages and disadvantages of the current routing schemes of FANETs, with a spectrum of standalone collision-avoidance schemes and bio-inspired optimization schemes to geographic schemes and protocols derived on the basis of MANETs. The two issues of trustworthy communication and collision avoidance in 3D airspaces have not been studied by any research studies although each of the research scholars has provided valuable information including scalability, adaptability, or flight safety.

The suggested BI-CAR protocol fulfils the primary gap between network-layer routing and physical-layer safety by integrating bio-inspired optimisation and real-time collision risk evaluation, to facilitate safer and more efficient UAV operations.

Table 1. Comparison of Existing Routing Protocols / Approaches in FANETs

Approach / Protocol	Strengths	Limitations in FANETs	Relevance to Proposed Work
MANET/VANET Protocols (AODV, DSR, OLSR, DSDV)	Mature, well-tested; efficient in ground-based scenarios	Poor performance under high mobility; no 3D spatial awareness; frequent link breakages [8][9]	Highlighted need for FANET-specific designs with mobility prediction and adaptive routing
Proactive Routing (OLSR, DSDV)	Immediate route availability; continuous topology knowledge	High control overhead; outdated info in fast-changing airspace; bandwidth waste [10]	Motivates shift toward more adaptive and lightweight routing
Reactive Routing (AODV, DSR)	On-demand route discovery reduces overhead; better suited for dynamic networks	Route discovery delays; weak adaptation to rapid changes; ignores collision risks [10]	Provides baseline but lacks collision awareness and spatial coordination

Geographic / Position-Based Routing (GPSR)	No routing tables; simple and scalable; location-based forwarding	Fails in high mobility; outdated GPS data; no collision consideration [11]	Indicates need for trajectory prediction and collision-aware metrics
Trajectory Prediction / LAR	Improves route accuracy; reduces search overhead	Ignores UAV speed, altitude, direction, obstacle proximity; limited collision dynamics [12]	Encourages integration of spatiotemporal awareness into routing
Bio-Inspired Optimization (ACO, PSO, ABC)	Decentralized, adaptive, resilient; supports multi-objective optimization (QoS, energy, hop count) [13–15]	QoS-focused; lacks collision avoidance; no real-time spatial separation [16]	Basis for proposed bio-inspired collision-aware routing protocol
Existing Collision Avoidance Methods (Reactive maneuvers, centralized control, local sensing)	Improve flight safety; handle local collision risk	Independent of routing layer; lack network-layer integration; poor scalability in swarms [17]	Motivates combining collision awareness with routing decisions
Proposed BI-CAR (Bio-Inspired Collision-Aware Reactive Routing)	Integrates bio-inspired optimization with real-time collision risk assessment; decentralized, adaptive, collision-aware routing; balances communication efficiency with flight safety	Yet to be validated under large-scale real-world UAV swarms	Novel contribution that unifies routing and collision avoidance for safe and efficient FANET operations [18]

Figure 1 shows that the proposed BI-CAR protocol will fill the gap between traditional routing protocols and independent collision avoidance schemes.

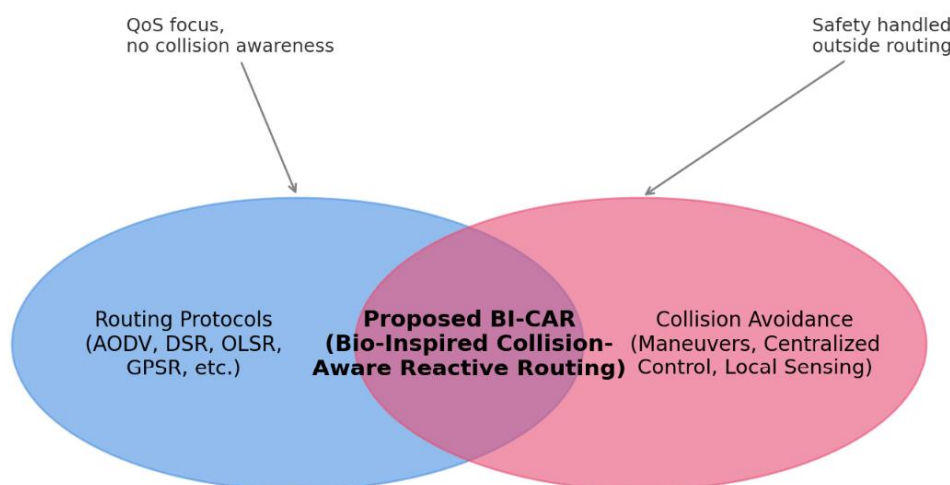


Figure 1. Bridging the Gap Between Routing and Collision Avoidance in FANETs

3. PROPOSED PROTOCOL : BI-CAR

It is a fact that FANETs are challenging, as compared to the conventional Mobile Ad Hoc Networks (MANETs), or Vehicular Ad Hoc Networks (VANETs). FANETs UAVs are highly dynamic, operate in a three-dimensional space, and have limited resources. The ability of the mid-air collisions of UAVs to affect the success of the mission makes routing decisions to ensure physical flight safety and communication efficiency. In fact, most of the existing routing protocols put more emphasis on the QoS metrics (e.g., packet delivery ratio, latency), and do not consider the safety-related issues (e.g., the overlap of trajectories and the risk of collision).

To bridge this gap, the Bio-Inspired Collision-Aware Reactive Routing (BI-CAR) protocol is introduced as the most appropriate routing paradigm which interconnects the communication reliability with the real-time collision avoidance. Using the opposite rules of routing algorithms, BI-CAR uses swarm intelligence rules by looking at the collective navigation of birds and insects. The methodology causes the UAVs to arrive at probabilistic, adaptive and decentralized routing decisions concerning the spatial safety and network performance. BI-CAR guarantees that not only the best routes are chosen to deliver data, but also that these routes are safe by nature to navigate with UAV.

To top it all, BI-CAR is largely reactive in the event of route generation where data transfer is required such as AODV. This slows down the speed of aerial networks. Furthermore, BI-CAR also uses CLC as opposed to the traditional reactive techniques. It undermines two important aspects (i) Collision Risk Index (CRI) that predicts UAV trajectory conflicts and (ii) connection dependability just to predict UAV trajectory conflicts that favors dual-metric appraisal.

It is discovered that the suggested BI-CAR protocol is completely different to the current routing systems in a number of ways. The "Collision-aware path evaluation has analysed every possible ways by making use of a real-time risk score which shows the relative motion of UAVs. The approach keeps the aircraft safe separation distances and minimizes the aerial confrontations. To further the argument, "swarm optimization" is also integrated into BI-CAR in investigating altered PSO mechanism that improves the various routing options as well as balancing problems such as flight safety, energy consumption, and route stability. Also, there is another significant attribute known as distributed spatial awareness whereby, UAVs only provides a certain mobility information to adjacent nodes, including their positions and velocity vectors.

Peer-to-peer prediction model with decentralized BI-CAR avoids the burden of collision, rather than central hub. Its key feature is the highlighting innovation, which is adaptive scalability, which employs pheromone evaporation and reinforcement to dynamically optimize routing tables. It is extensively used and applied to the mission-critical scenarios such as disaster response by prioritising the communication and navigation twice. In order to discuss further on this, the architecture of the algorithm has been detailed in the further study along with the mathematical explanation of the CRI and CLC measures.

3.1. Design Objectives and Methodology

As it has been mentioned earlier, in FANETs, the BI-CAR protocol tries to strike a balance between network communication efficiency and aerial safety. BI-CAR introduces a multi-objective design paradigm which considers the data delivery dependability, mobility stability and collision avoidance simultaneously.

Just like AODV in theory, the protocol adheres to a reactive routing model, in which routes are only found when a source UAV needs to communicate with a destination. This minimizes the overhead of unnecessary control messages and is especially significant in the aerial topology that changes. Bio-inspired swarm optimization is applied to dynamically identify the optimal routes after the implementation, which subsequently makes UAVs adapt intelligently to the existing environmental and network conditions.

3.1.1. Collision-Aware Path Evaluation

In this, BI-CAR checks whether there are any collision hazards on every path in the route finding process. Depending on their relative motion characteristics such as position, velocity and direction, the collision risk indicator verifies that UAVs in a path are prone to collide with each other hazardously. This active process enables the rejection of unsafe routes even prior to their formation and also ensures that the chosen routes have a sufficient separation among UAVs. This mechanism goes a long way in enhancing safety in the air and minimizing chances of congestion in the mid-air.

3.1.2. Swarm Optimization Integration

Since this study primarily aims at incorporating BI-CAR in a modified PSO algorithm, it guarantees the routing paths using collective UAV intelligence. The characteristics such as position, velocity and path alignment, the risk of collision involving UAVs measure evaluates the possibility of it approaching dangerously close to the other. This process can also omit hazardous paths and

make sure that the selected paths maintain UAVs at a reasonable distance and periodically refresh them as well. Such results reduce the chances of collision-free paths and enhance aerial security particularly when deploying UAVs in large numbers.

3.1.3. Distributed Spatial Awareness

UAVs in BI-CAR communicate miniature mobility beacons to facilitate collision prediction in a non-centralized manner, spatial data, to be precise, position and velocity vectors. This local information assists every UAV with a small-range awareness field and facilitated it to calculate the possible collision threats on its own. Through this approach, scalability, robustness and minimal communication overheads are guaranteed. Although it can be used to work well even without a permanent ground infrastructure, this makes BI-CAR suitable to mission critical and infrastructureless missions like search and rescue or reconnaissance.

3.1.4. Adaptability and Scalability

The most effective adaptive quality was applied in BI-CAR based on the behavior of ants in nature. UAVs strengthen such pathways by increasing the values of pheromones associated with them, and effectively passing data. The trails of stronger pheromone show the paths which are always stable, efficient and safe. Due to the evaporation of pheromones, inferior pathways on the other hand are being eliminated slowly. Such adaptations guarantee scalability to a collection of densities of UAVs, both small collaborative groups and large, multifaceted aerial swarms.

3.2. System Model

The suggested BI-CAR protocol operates on a FANET comprising of N autonomous Unmanned Aerial Vehicles (UAVs). The point to note is that in three-dimensional (3D) space, every UAV is a mobile node that has self-organizing features in navigation and communication. GPS receivers, onboard CPUs, inertial sensors and wireless transceivers are being fitted in order to enable local decision-making and flight control. Position, velocity, and identification information of each UAV are also included and periodically transmitted in beacon messages of its current kinematic state.

Position Vector : $\vec{p}_i(t) = (x_i(t), y_i(t), z_i(t))$

Velocity Vector : $\vec{v}_i(t) = (v_{xi}, v_{yi}, v_{zi})$

Unique Node Identifier : ID_i

The nearby UAVs are able to predict relative movement patterns and approximate spatial awareness thanks to these recurring updates. UAVs used line-of-sight (LoS) to communicate with each other over a fixed transmission range R, which is the maximum range over which direct packet exchange is possible. The network supports the following assumptions.

Small Range of Communication: UAVs can only communicate directly with each other in case the Euclidean distance $d_{ij} \leq R$. Reactive Routing: Needless control overhead is minimised. An infrastructure-less topology is one in which, independent of a centralized controller, all routing decisions are made distributively. Dynamic Mobility: UAVs can move in any direction of the three-dimensional space and thus the topologies are rapidly varied. Safety-Aware Communication: UAVs remarkably alter their adjust paths and a minimum distance between them to avoid collisions. It eventually makes BI-CAR capable of supporting on-demand route discovery, consistent link assessment, collision forecasting, and scalability of dense UAV swarms.

3.2.1. UAV Mobility Modeling Using the 3D Gauss – Markov Process

The model is useful in realistic UAV flight patterns, in which there is a temporal correlation between velocity and direction. At a discrete time period t, the velocity and angular direction of UAV i are represented as in Eq. (1) and Eq. (2).

BI-CAR has been analysed correctly to assume the 3D Gauss-Markov Mobility Model, which introduces controlled randomness and preserves the continuity of trajectories; the model has been used to model UAV mobility in aerial space. In real-life, UAV flight patterns, where velocity and direction are both temporally related and these are well represented by this model. The angular direction and velocity of UAV I at any time step, t, are given in Eq. (1) and (2).

$$v_i(t) = \alpha v_i(t - \Delta t) + (1 - \alpha) \vec{v} + \sqrt{(1 - \alpha^2)} w_v \quad (1)$$

$$\theta_i(t) = \alpha \theta_i(t - \Delta t) + (1 - \alpha) \vec{\theta} + \sqrt{(1 - \alpha^2)} w_\theta \quad (2)$$

where, $\alpha \in [0,1]$ is the temporal dependency factor, controlling the smoothness of motion. $\vec{v}$ and $\vec{\theta}$ are the mean velocity and direction. w_v and $w_\theta \sim N(0,1)$ are Gaussian random variables introducing randomness. The updated 3D position of UAV i after a time interval Δt is given in Eq. (3).

$$\vec{p}_i(t + \Delta t) = \vec{p}_i(t) + v_i(t) \cdot [\cos(\theta_i(t)) \cos(\phi_i(t)), \sin(\theta_i(t)) \cos(\phi_i(t)), \sin(\phi_i(t))] \cdot \Delta t \quad (3)$$

This will give a realistic flight behavior where the velocity and direction change slowly, and there are no sudden transitions that may result in instability. 3D Gauss Markov UAV Mobility Update as shown in Algorithm 1.

Algorithm 1. 3D Gauss–Markov UAV Mobility Update

Input:

- Initial position $\vec{p}_i(0)$, initial velocity $v_i(0)$, mean values $\bar{v}$, $\bar{\theta}$, dependency factor α , and time step Δt .

Output : Updated position $\vec{p}_i(t + \Delta t)$, updated velocity $v_i(t + \Delta t)$

Algorithm:

1. Generate Gaussian random variables $w_v, w_\theta \sim N(0, 1)$.
 2. Update velocity and direction using Eq. (1) and Eq. (2).
 3. Compute new position using Eq. (3).
 4. Repeat for each UAV at every time interval Δt .
-

3.3. Collision-Aware Routing Metric

In FANETs, it is necessary that preserving communication connections without jeopardizing the safety of flights is very important. BI-CAR presents a CRI, which is a metric of the probability of two UAVs flying in a dangerously close fashion relative to each other during flight. Relative motion parameters are used by the CRI to identify possible collision hazards.

3.3.1. Collision Risk Index (CRI) Definition

The given two UAVs i and j with position vectors $\vec{p}_i(t)$ and $\vec{p}_j(t)$, velocity vectors $\vec{v}_i(t)$ and $\vec{v}_j(t)$ generates a value ranging from 0 (no risk) to 1 (highest risk).

Compute Relative Position

$$\vec{p}_{rel} = \vec{p}_i - \vec{p}_j \quad (4)$$

Eq. (4) provides the vector difference between the positions of the two UAVs.

Compute Relative Velocity

$$\vec{v}_{rel} = \vec{v}_i - \vec{v}_j \quad (5)$$

Eq. (5) shows the fast rate at which UAV i is moving towards UAV j .

Compute Time to Closest Point of Approach (TCPA)

$$t_{CPA} = - \frac{\vec{p}_{rel} \cdot \vec{v}_{rel}}{\|\vec{v}_{rel}\|^2 + \varepsilon} \quad (6)$$

The time of nearest approach between UAVs is calculated by their current movement. In particular, the denominator normalizes the measures; conversely the dot product is used to measure the similarity in the direction of their motion vectors. It is determined that when t_{CPA} is negative, the UAVs have already passed the point of minimum distance. The mathematical formula of such calculations is presented in Eq. (6).

Compute Distance at Closest Point of Approach (DCPA)

$$d_{CPA} = \|\vec{p}_{rel} + t_{CPA} \cdot \vec{v}_{rel}\| \quad (7)$$

The distance between the UAVs at the point of closest approach (d_{CPA}) is calculated using Eq. (7).

Compute the Collision Risk Index

$$CRI = \begin{cases} 1 - \frac{d_{CPA}}{d_{thresh}}, & \text{if } 0 < t_{CPA} < t_{thresh} \text{ and } d_{CPA} < d_{thresh} \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

CRI is a scaling risk score, when the UAVs are supposed to be exceptionally close within the time and distance constraints. Otherwise, the risk is less and is determined in Eq. (8). An example of the Collision Risk Index Computation is explained in Algorithm 2.

Algorithm 2. Computation of Collision Risk Index

Input:

- Position and velocity vectors $(\vec{p}_i, \vec{v}_i)$, $(\vec{p}_j, \vec{v}_j)$, safety thresholds d_{thresh} , t_{thresh} .

Output : Collision Risk Index CRI_{ij} .

Algorithm:

1. Compute relative position $\vec{p}_{rel} = \vec{p}_i - \vec{p}_j$.
2. Compute relative velocity $\vec{v}_{rel} = \vec{v}_i - \vec{v}_j$.
3. Evaluate t_{CPA} using Eq. (6).
4. Evaluate d_{CPA} using Eq. (7).
5. If $(0 < t_{CPA} < t_{thresh})$ and $(0 < d_{CPA} < d_{thresh})$:
 Compute $CRI_{ij} = 1 - (d_{CPA} / d_{thresh})$.
- Else
 Set $CRI_{ij} = 0$.

6. Return CRI_{ij} .
-

Interpretation and Integration

Potential collision threats are filtered in route discovery with the calculated CRI values by unsafe links resulting in a potential collision. Routes whose cumulative CRI is above a threshold β are removed. This reduces link-stable and flight-safe in addition to reducing packet loss in the area around UAVs or flight paths overlap.

BI-CAR integrates kinematic prediction, mobility awareness, and network routing efficiency, offering one framework of safe and energy-balanced communication in dynamic aerial networks through the integration of CRI into the route selection stage.

3.3.2. Composite Link Cost

BI-CAR integrates collision-aware routing and swarm intelligence into one decision measure by the use of the CLC model. The UAVs are inspired by the ACO: the CRI is used to allocate the routing decisions based on the two important factors path reliability through pheromone reinforcement and collision safety. Such hybridization allows UAVs to choose the routes that can guarantee the high level of communication and the safe spatial distance without any centralized coordination and the overall view of the network. In this respect, BI-CAR embraces two fundamental bio-inspired principles.

Pheromone-Based Path Reinforcement

The intensity of pheromones and the associated connection enhance the intensity of pheromones indicating its reliability and efficacy. It is known that the increased level of pheromones will be more preferred in the future discoveries of the routes, which stimulate the use of the effective and reliable routes.

Collision-Aware Neighbour Evaluation

UAVs evaluate potential next hops for route discovery based on relative position and motion. Roads that go through congested or dangerous areas are punished due to the CRI that is recalculated on the fly.

These methods enable UAVs to enable decentralized, adaptive and safety-aware routing such that it can dynamically integrate their communication patterns despite high mobility or interference.

Composite Link Cost Formulation

The fundamental of BI-CAR is a CLC statistic which combines real-time collision risk and pheromone preference. This measure is determined by the approach mentioned in Eq. (9).

$$CLC_{ij} = \alpha \cdot \varphi_{ij}^{-1} + \beta \cdot CRI_{ij} \quad (9)$$

Where

CLC_{ij} : The composite cost of forwarding data from UAV i to UAV j.

φ_{ij} : The pheromone intensity on the link (i,j) represents its past performance.

$CRI_{ij} \in [0,1]$: Collision Risk Index between UAVs i and j, as defined below.

$\alpha, \beta \in [0,1]$: Weighting factors such that $\alpha + \beta = 1$.

It is discovered that it is a more favorable route implies greater reliability of communication and reduced probability of collision and it is characterized by smaller CLC_{ij} values. This role has a direct influence on the swarm-based path selection in the following step such that the optimal route discovered by BI-CAR. It is simultaneously collision-free, stable, and energy-efficient. Algorithm 3 shows the calculation of Composite Link Cost of BI-CAR.

Algorithm 3. Computation of Composite Link Cost

Input:

- φ_{ij} : Current pheromone concentration on link (i, j).
- CRI_{ij} : Collision Risk Index between UAVs i and j.
- α, β : Weighting coefficients where $\alpha + \beta = 1$.
- Neighbor set N_i : List of all UAVs within range of UAV i.

Output : CLC_{ij} : Composite Link Cost for each neighbor $j \in N_i$.

Algorithm:

1. Initialize pheromone and CRI tables for UAV i.
 2. For each neighbor $j \in N_i$:
 - Retrieve φ_{ij} and CRI_{ij} .
 - Compute inverse pheromone : $P_{pher} = \varphi_{ij}^{-1}$.
 - Compute composite cost : $CLC_{ij} = \alpha \cdot \varphi_{ij}^{-1} + \beta \cdot CRI_{ij}$.
 - Store CLC_{ij} in the routing table.
 3. Normalize if required $CLC'_{ij} = \frac{CLC_{ij}}{\sum_{k \in N_i} CLC_{ik}}$.
 4. Forward all CLC_{ij} to the Swarm Optimization module for route selection.
-

The algorithm 3 allows UAVs to continuously evaluate link quality by blending two real-time measurements :

1. Pheromone term (φ_{ij}^{-1}) captures link reliability and past success.

2. Collision risk term (CRI_{ij}) guarantees safeness by penalizing risky or congested flight paths. Consequently, CLC_{ij} , acts as a unified cost function for the swarm-based routing heuristic (Section 3.4), where favours with the lowest cost during the path discovery and selection process. BI-CAR maintains adaptive, safe, and efficient routing even in rapidly changing FANET topologies even in quickly evolving FANET topologies.

3.4. Swarm-Based Route Optimization in BI-CAR

The Bio-Inspired Collision-Aware Reactive Routing (BI-CAR) protocol integrates safe navigation and efficient routing in dynamic aerial settings by exploiting swarm intelligence. UAVs are cooperative, as is seen in biological swarms like ants, birds and bees. Every UAV is able to self-organize, evolve, and communicate without collisions, even in congested airspaces.

3.4.1. Principle of Swarm Intelligence in BI-CAR

BI-CAR behavioral foundation is offered by Swarm intelligence. Every UAV acts as a local agent to perceive its environment as well as interact with neighbours and affect the actions of the whole system at the local level. Typically, ants follow pheromone trails so as to maximize the food collection, and birds coordinate their speeds to avoid collisions. BI-CAR realizes these concepts digitally and guarantees it through the creation of a Virtual Pheromone Field and a Collision-Aware Routing Environment.

It is known that BI-CAR protocol modifies the fundamental concepts of of swarm intelligence to allow effective, self-organizing communication between UAVs. It is discovered that, every UAV is autonomous and connects its next hop depending on the local pheromone strength and the link cost. In this dynamic way, UAVs respond to the changes in the mobility, topology, and airspace conditions by dynamically updating their pheromone intensities and collision risk metrics. In total, these characters permit an emergent global optimization, in which the network makes use of the cumulative effect of simple local interactions.

3.4.2. Virtual Pheromone Table (VPT)

Every UAV keeps a Virtual Pheromone Table (VPT), which contains the values of pheromone intensity ϕ_{ij} , CLC and CRI of the neighbour j .

$$VPT_i = \{(j, \phi_{ij}, CLC_{ij}, CRI_{ij}) \mid j \in N_i\} \quad (10)$$

The dynamics of pheromone intensities depend on link reliability and safety. Pheromone reinforcement occurs upon successful packet forwarding, as shown in Eq. (11).

$$\phi_{ij}(t+1) = (1-\rho)\phi_{ij}(t) + \frac{Q}{CLC_{ij}} \quad (11)$$

where ρ is the pheromone evaporation coefficient and Q is a reinforcement constant. This ensures that safe, stable links (low CLC_{ij}) gain higher pheromone reinforcement.

Links that are idle or exhibit increasing collision risks undergo decay.

$$\phi_{ij}(t+1) = (1-\rho)\phi_{ij}(t) \quad (11a)$$

The VPT thus enables UAVs to maintain a distributed awareness of reliable and safe connections while keeping communication overhead minimal.

3.4.3. Collision-Aware Route Discovery Process

The collision risk is included in the reactive route finding phase of BI-CAR. A source UAV sends a Route Request (RREQ) packet with its pheromone and current values of risk.

$$RREQ = \{\text{SourceID}, \text{DestID}, \text{SeqNo}, \text{HopCount}, CLC_{\text{path}}, \phi_{\text{path}}, CRI_{\text{path}}\}$$

Upon receiving an RREQ, each UAV performs the following.

Risk Evaluation: Calculates the CRI using relative velocity and position vectors (v_i, p_i) and the predicted Time to Closest Point of Approach (TCPA) and Distance at Closest Point of Approach (DCPA).

$$CRI_{ij} = e^{-\lambda \cdot (DCPA_{ij} / TCPA_{ij})} \quad (12)$$

Composite Link Cost Calculation:

$$CLC_{ij} = \alpha \cdot \varphi_{ij}^{-1} + \beta \cdot CRI_{ij} \quad (13)$$

where $\alpha + \beta = 1$. Lower CLC_{ij} values indicate better balance between reliability and safety.

Probabilistic Next-Hop Selection : Each UAV probabilistically selects its next hop based on pheromone strength and inverse link cost expressed in Eq. (14).

3.4.4. Probabilistic Path Selection

BI-CAR uses as a forwarding mechanism based on probabilistic movement of ants in ACO, to ensure flexibility and prevent routing loops. P_{ij} is the probability of a UAV i to use neighbor j as the next hop

$$P_{ij} = \frac{(\phi_{ij})^{\alpha_1} (1/CLC_{ij})^{\beta_1}}{\sum_{k \in N_i} (\phi_{ik})^{\alpha_1} (1/CLC_{ik})^{\beta_1}} \quad (14)$$

where α_1 and β_1 represent the influence of pheromone intensity and link cost and N_i is the neighbor set of UAV i .

It finally makes sure that UAVs preferentially choose collision-safe and communication-efficient links with a limited exploration of alternative paths to be found to accommodate dynamic changes

3.4.5. Swarm-Based Route Optimization Algorithm

Swarm-Based Reactive Routing of FANET BI-CAR can be seen in Algorithm 4.

Algorithm 4. BI-CAR Swarm-Based Reactive Routing

Input:

- ϕ_{ij} : pheromone intensity, CRI_{ij} : Collision Risk Index, CLC_{ij} : Link Cost, N_i : Neighbor set, Parameters : ρ , Q , α_1 , β_1 .

Output : Optimized next-hop j^* , updated pheromone table $\varphi_{ij}(t+1)$.

Algorithm:

1. Initialization : Each UAV initializes its pheromone table with equal values and computes CLC_{ij} for all neighbors using Eq. (13).
 2. Route Discovery : Source UAV broadcasts RREQ including CLC_{path} , ϕ_{path} , CRI_{path} .
 3. Neighbor Evaluation : Upon RREQ reception, UAV computes CRI_{ij} , updates CLC_{ij} and calculates forwarding probability P_{ij} using Eq. (14).
 4. Probabilistic Forwarding : The UAV selects the next hop j^* with maximum P_{ij} .
 5. Reinforcement Update : If packet transmission succeeds, pheromone is updated as per Eq. (11).
 6. Evaporation : For inactive links, pheromone decays as per Eq. (11a).
 7. Route Maintenance : When high CRI or link failure occurs, UAV triggers local repair or new route discovery.
 8. Termination : The route with the minimum cumulative CLC_{path} and highest pheromone concentration becomes the preferred communication path.
-

When introducing swarm intelligence to BI-CAR, UAVs naturally work together to ensure safe and efficient communication the requirement of international coordination. The Probabilistic Path Selection enhances premature convergence and decentralized awareness. BI-CAR may be used effectively with pheromone-based reinforcement, collision-conscious measures, and reactive discovery. This synergy enables BI-CAR to be superior to conventional reactive protocols with regard to route stability, safety, and adaptability features that are crucial to mission-critical FANET applications.

3.5. BI-CAR Integrated Routing Algorithm

The BI-CAR protocol is very compatible with the CRI, CLC, pheromone reinforcement, and PSO into the optimal routing process. The three synchronized 3R steps include; Route Discovery, Route Optimization, and Route Maintenance, that guarantee that the chosen paths optimize the efficiency of communication and flight safety in highly dynamic FANET environments.

3.5.1. Mathematical Flow and Functional Overview

Each UAV U_i records the track of neighbor information and corresponding pheromone intensities $\phi_{ij}(t)$ in a Virtual Pheromone Table (VPT). When a source UAVs broadcasts a Route Request (RREQ) packet containing its location, velocity vector, and a timestamp, it starts with data transmission.

$$CRI_{ij} = 1 - e^{-\left(\frac{DCPA_{ij}}{d_{th}}\right)^2 + \left(\frac{TCPA_{ij}}{t_{th}}\right)^2} \quad (15)$$

where $DCPA_{ij}$ and $TCPA_{ij}$ denote the Distance and Time to Closest Point of Approach, and d_{th} , t_{th} are safety thresholds. Each link is then evaluated by the CLC model Eq. (13).

$$CLC_{ij} = \alpha \cdot \phi_{ij}^{-1} + \beta \cdot CRI_{ij} \quad (13)$$

where $\alpha+\beta=1$, ensuring a weighted balance between link reliability and collision risk. Lower CLC_{ij} values indicate more desirable routes.

Once all feasible paths are constructed, PSO-based optimization refines the selection. Each candidate's route R_k is represented as a particle with a position vector X_k (encoding node sequence) and a velocity vector V_k (representing the probability of neighbor substitution). The fitness of each route is computed as Eq. (16).

$$f(R_k) = \frac{\omega_1 \cdot PDR(R_k)}{\omega_2 \cdot E_{avg}(R_k) + \omega_3 \cdot CRI_{avg}(R_k)} \quad (16)$$

where ω_1 , ω_2 , ω_3 are tunable weights reflecting throughput, energy consumption, and collision safety priorities. The swarm iteratively updates as Eq. (17) and Eq. (18).

$$V_k(t+1) = \omega V_k(t) + c_1 r_1 (P_{best} - X_k(t)) + c_2 r_2 (G_{best} - X_k(t)) \quad (17)$$

$$X_k(t+1) = X_k(t) + V_k(t+1) \quad (18)$$

The global best particle G_{best} represents the final optimized route from source to destination. Finally, pheromone reinforcement occurs along the selected route expressed in Eq. (19).

$$\phi_{ij}(t+1) = (1 - \rho)\phi_{ij}(t) + \Delta\phi_{ij} \quad (19)$$

where ρ is the pheromone evaporation rate and $\Delta\phi_{ij} = \frac{Q}{CLC_{ij}}$ with Q being a constant reward factor. This process frequently enhances successful and safe paths while gradually eliminating unsafe or unreliable ones. BI-CAR Integrated System Algorithm (Design Phase) is illustrated in Algorithm 5. The main objective is to integrate collision prediction, link-cost evaluation, pheromone-based learning, and swarm-inspired PSO optimization into a unified adaptive routing framework.

Algorithm 5. BI-CAR Integrated System Algorithm

Input:

- N : Total number of UAVs.
 - $P_i(t)$, $V_i(t)$ Position and Velocity of UAV i .
 - ϕ_{ij} : Pheromone intensity on link (i, j) .
-

- α, β : Weighting factors for link cost (communication vs. collision).
- ρ : Evaporation rate.
- θ : Reinforcement constant.
- PSO_params : Swarm Parameters ($\omega, c1, c2$).

Output : Optimized collision-aware route R^* with minimum CLC and safe connectivity.

Algorithm:

1. Initialize UAV swarm : Assign initial positions, velocities, and pheromone levels $\phi_{ij}(0)$ for all links.

2. Evaluate Relative Motion :

For each UAV pair (i, j) :

$$p_{rel} = p_j - p_i, v_{rel} = v_j - v_i$$

Compute time to closest point of approach (TCPA) :

$$t_{CPA} = -\frac{\vec{p}_{rel} \cdot \vec{v}_{rel}}{\|\vec{v}_{rel}\|^2 + \varepsilon}$$

and distance at closest approach :

$$d_{CPA} = \|\vec{p}_{rel} + t_{CPA} \cdot \vec{v}_{rel}\|$$

3. Collision Risk Index :

$$CRI = \begin{cases} 1 - \frac{d_{CPA}}{d_{thresh}}, & \text{if } 0 < t_{CPA} < t_{thresh} \text{ and } d_{CPA} < d_{thresh} \\ 0, & \text{otherwise} \end{cases}$$

4. Compute Composite Link Cost :

For each link (i, j) :

$$CLC_{ij} = \alpha \cdot \phi_{ij}^{-1} + \beta \cdot CRI_{ij}$$

Lower CLC_{ij} indicates more efficient and safer communication.

5. Particle Swarm Optimization for Path Refinement :

5.1. Initialize particles as candidate routes.

5.2. Evaluate fitness $f(R_k) = \sum CLC_{ij}$ for Route R_k .

5.3. Update velocity and position using :

$$V_k = \omega V_k + c_1 r_1 (Pbest_k - R_k) + c_2 r_2 (G_{best} - R_k)$$

$$R_k = R_k + V_k$$

5.4. Iterate until convergence to R^* .

6. Update Pheromone Table :

For each link (i, j) in the optimal route :

$$\phi_{ij}(t+1) = (1 - \rho)\phi_{ij}(t) + \frac{Q}{CLC_{ij}}$$

7. Output Optimal Route :

Return optimized route R^* with minimal CLC and safe inter-UAV separation.

The combination of localized intelligence and global stability is integrated in BI-CAR. In its course, the CRI component enhances flight safety as CLC ensures connection dependability. Further, Pheromone reinforcement promotes adaptive learning over time, unlike PSO optimization that offers global information using distributed fitness assessment. Such a combination allows BI-CAR to provide dynamic control of communication performance, energy efficiency and spatial safety which are essential to mission critical FANET applications.

4. BI-CAR ROUTING ALGORITHM

BI-CAR protocol is designed to meet the unique demands of FANETs, in which UAVs are highly mobile, have dynamic topology, and unreliable links. BI-CAR combines swarm intelligence, collision prediction and probabilistic optimization to create safe and energy efficient communication connections. The routing process is broken down into three operational phases namely Route Discovery, Selection and Reinforcement of Routes, and Local Recovery and Route Maintenance. BI-CAR is a hybrid reactive system whereby the routes are only created when needed, minimizing the control overhead that is unnecessary, and maintaining adaptivity with pheromone-based and risk-aware decision-making.

4.1. Route Discovery

In aerial environments, it is not possible to maintain complete topology knowledge throughout its process. This is why BI-CAR uses reactive path discovery mechanism, which is only activated when a source UAVs wants to communicate with a destination D and there is no valid path in the routing cache. The source node links a Path Discovery Packet (PDP) with the following information: Source identifiers and destination identifiers, Sequence number and timestamp, Visited UAVs list (to prevent loops), and Path cost accrued.

Each intermediate UAV i that receives the PDP performs localized route evaluation. For every neighbour j , the CLC is calculated as expressed in Eq. (13). A lower CLC_{ij} reflects a more favourable link, balancing communication reliability and collision safety.

$$CLC_{ij} = \alpha \cdot \varphi_{ij}^{-1} + \beta \cdot CRI_{ij} \quad (13)$$

Each UAV probabilistically selects the next-hop neighbour j using Eq. (14).

$$P_{ij} = \frac{\tau_{ij}^{\gamma} / c_{ij}^{\delta}}{\sum_{k \in N_i} \tau_{ik}^{\gamma} / c_{ik}^{\delta}} \quad (14)$$

where τ_{ij} is pheromone strength, c_{ij} is the link cost, and γ, δ are influence parameters controlling the relative bias toward pheromone versus cost.

A roulette-wheel stochastic mechanism is used to select the next hop, so that paths are not explored in a similar way. After several PDPs have arrived at the destination D, the PDP with the least total cost and largest pheromone reinforcement will be the primary route.

4.2. Route Selection and Reinforcement

When the destination UAV D receives successful PDPs, it sends a Path Back Packet (PBP) which reverses the path that it had found to the source S. The nodes on this path back update their local pheromone table according to the route quality of the route in Eq. (19).

$$\tau_{ij}(t+1) = (1 - \rho) \cdot \tau_{ij}(t) + \frac{\theta}{CLC_{ij}} \quad (19)$$

where ρ represents pheromone evaporation rate, enabling adaptation to topological dynamics and θ is a positive reinforcement constant, strengthening paths with lower costs.

Their probability of being selected in the transmissions can be enhanced by successful and collision-free links. Positive feedback amplifies effective ways leading to behaviour reflections of biological swarm systems, evaporation offers flexibility, avoiding stagnation and encouraging search of alternative paths.

4.3. Route Maintenance and Local Recovery

The difficult thing is that the mobility of UAVs and the disturbance of the environment usually lead to a break in the links during data transfer. In this case, BI-CAR is used to monitor the quality of links and CRI in real time. A Partial Path Discovery Process (Partial PDP) is launched when the CRI of a link is above a threshold (CRI_{th}), and this indicates that the link is unstable or in an unsafe position.

It is a local repair process that builds sub-paths around the damaged area without flooding the entire world so that communication is not disrupted. Pheromone values on failed links are decayed with the help of the Eq. (20) to avoid dependence on unsteady paths in the future.

$$\tau_{ij}(t+1) = (1 - \rho) \cdot \tau_{ij}(t) \quad (20)$$

The local recovery stage also improves the resilience of the network by reducing the loss and delay of packets, supporting the continuity of the flows, and avoiding the entry of UAVs into the high-risk or collision-prone areas.

4.4. Algorithm – BI-CAR Integrated Routing

Algorithm 6. BI-CAR

Input:

- Source UAV S, destination UAV D.
- Parameters $(\alpha, \beta, \rho, \theta, \gamma, \delta)$.
- Pheromone table τ_{ij} , CRI threshold CRI_{th} .

Output : Optimal path P^* between S and D with minimum composite cost and maximum safety.

Algorithm:

1. Route Discovery Phase
 - 1.1. Initialize PDP = [S, D, path = {S}, cost = 0].
 - 1.2. Source S broadcasts PDP to neighbours.
 - 1.3. For each intermediate UAV i receiving PDP.
 - 1.3.1. Discard duplicate or looping packets
 - 1.3.2. For each neighbour $j \in N_i$:

Compute $CLC_{ij} = \alpha \cdot \varphi_{ij}^{-1} + \beta \cdot CRI_{ij}$
 Compute forwarding probability P_{ij} using Eq. (14).
 - 1.3.3. Select next-hop j probabilistically (roulette-wheel).
 - 1.3.4. Update PDP.path and PDP.cost.
 - 1.3.5. Forward PDP to j.
2. Route Selection and Reinforcement
 - 2.1. Destination D receives multiple PDPs.
 - 2.2. Select route P^* with minimum total $\sum CLC_{ij}$.
 - 2.3. Generate PBP and traverse P^* back to S.
 - 2.4. For each (i, j) in P^* :

Update $\tau_{ij}(t+1) = (1 - \rho) \cdot \tau_{ij}(t) + \frac{\theta}{CLC_{ij}}$.
3. Route Selection and Reinforcement
 - 3.1. During transmission, monitor link CRI.
 - 3.2. If $CRI_{ij} > CRI_{th}$:

Initiate Partial PDP from node i.
 Decay pheromone : $\tau_{ij}(t+1) = (1 - \rho) \cdot \tau_{ij}(t)$.
 - 3.3. Continue transmission using repaired sub-route.

End Algorithm

4.5. Comparative Evaluation : BI-CAR Vs. Traditional Routing Protocols

More common protocols like AODV, DSR, and OLSR use deterministic route selection which may be hop-count based or delay based and do not have a dynamic collision awareness mechanism. The mobility-sensitive variants such as GPSR do add positional metrics, but do not solve predictive risk modeling or adaptive pheromone learning. Conversely, BI-CAR produces decentralized probabilistic routing decisions, which is a combination of collision prediction and stigmergic reinforcement. Table 2. sums up the technical differences.

Feature / Metric	Traditional Protocols (AODV/OLSR/DSR)	Mobility-Aware (MAR/GPSR)	BI-CAR
Decision Type	Deterministic	Predictive / Greedy	Probabilistic (swarm based)
Routing Type	Table-driven or on-demand	Position based	Reactive + adaptive
Communication Metric	Hop count or delay	Velocity, distance	Pheromone + CRI
Collision Awareness	None	Implicit (via motion)	Explicit (CRI-based)
Composite Metric	$C_{ij} = \text{HopCount}_{ij}$	$C_{ij} = \gamma \ v_i - v_j\ + \delta \ p_i - p_j\ $	$CLC_{ij} = \alpha \varphi_{ij}^{-1} + \beta CRI_{ij}$
Adaptivity	Periodic updates	Movement-based	Self-adaptive (pheromone + risk)
Scalability	Moderate	Medium	High
Collision Reaction	Not considered	Limited	Real-time prediction (CPA-based)
Forwarding Strategy	Fixed	Greedy	Probabilistic (based on pheromone + CRI)
Stigmergy / Indirect Learning	None	None	Yes (pheromone table)

Table 2 : Comparative Analysis - BI-CAR vs. Traditional Routing Protocols

4.5.1. Analytical Distinctions in Metric Formulation

Traditional Metric :

$$C_{ij} = \text{HopCount}_{ij}$$

Purely topological, lacks motion or reliability awareness.

Mobility-Aware Routing :

$$C_{ij} = \gamma \cdot \|v_i - v_j\| + \delta \cdot \|p_i - p_j\|$$

Considers relative velocity and position but omits predictive safety assessment.

BI-CAR Composite Metric :

$$CLC_{ij} = \alpha \cdot \varphi_{ij}^{-1} + \beta \cdot CRI_{ij}$$

Balances communication performance (pheromone) with collision risk (CRI), yielding a robust, adaptive cost function.

Collision Risk Prediction (Unique to BI-CAR)

$$CRI = \begin{cases} 1 - \frac{d_{CPA}}{d_{thresh}}, & \text{if } 0 < t_{CPA} < t_{thresh} \text{ and } d_{CPA} < d_{thresh} \\ 0, & \text{otherwise} \end{cases}$$

Where

$$t_{cpa} = - \frac{\vec{p}_{rel} \cdot \vec{v}_{rel}}{\|\vec{v}_{rel}\|^2 + \varepsilon}$$

$$d_{cpa} = \|\vec{p}_{rel} + t_{CPA} \cdot \vec{v}_{rel}\|$$

This enables proactive avoidance by predicting potential collision proximity.

Uniqueness of BI-CAR

- Combines swarm-inspired stigmergy with real-time collision risk prediction.
- Employs probabilistic route selection ensuring robustness and adaptability.
- Integrates positive/negative pheromone feedback for continuous learning.
- Supports partial local recovery for sustained communication under dynamic topology.
- Entirely decentralized, scalable, and computationally efficient.

5. PERFORMANCE EVALUATION

The effectiveness and scalability of the proposed BI-CAR protocol were tested with an extensive set of simulations with the help of the NS-3 network simulator, complemented with a custom three-dimensional UAV mobility module. The main objective of the evaluation is to evaluate the efficiency of communication and airspace safety in dynamic FANET conditions.

The routing protocols were benchmarked using three popular routing protocols. Whereby, AODV is a traditional reactive protocol which finds routes on demand, but does not adapt to 3D mobility. The second is that DSR (Dynamic Source Routing): It is another reactive method that uses source routing and caching techniques. The third routing protocols is that AntHocNet is a bio-inspired hybrid ACO-based protocol that incorporates reactive path setup and proactive pheromone reinforcement.

The use of pheromone concepts and the use of AntHocNet which is an inclusion make use of pheromone concepts and gives a bio-inspired baseline to compare. Also, it adds the integrated CRI, CLC, and swarm-intelligence-based optimization of the BI-CAR.

5.1. Simulation Setting

The entire simulations were conducted in a 3D working volume of 1500 m x 1500 m x 500m. In order to examine scalability, the UAV node count was changed between 50 and 500 in 50 steps. All the UAVs used a Random Waypoint 3D flight path with speeds between 10 m/s and 30 m/s and a pause time of 1 s to 5 s.

The simulations were conducted with 600 seconds and the average result was obtained after 10 independent seeds to achieve statistical reliability. UDP Constant Bit Rate (CBR) sources with a payload size of 512 bytes and an inter-packet delay of 0.1 s were used to generate communication traffic. The radio transmission of each UAV was set at 250 meters and IEEE 802.11s MAC protocol was used to enable multi-hop mesh forwarding. The emulation of realistic UAV dynamics was performed by a 3D mobility model based on Gauss-Markov and the smooth transition of heading and changes in altitude. The proposed BI-CAR was tested against AODV, DSR and AntHocNet in the same environment and traffic conditions.

Parameter	Value
Simulator	NS-3 v3.38
Simulation area	1500 m × 1500 m × 500 m (3D)
UAV nodes	50 – 500 (step 50)
Simulation time	600 s
UAV speed	10 – 30 m/s (Random Waypoint 3D)
Mobility model	Custom 3D Gauss-Markov
Traffic model	CBR (UDP)
Packet size	512 bytes
Transmission range	250 m
MAC protocol	IEEE 802.11s
Routing protocols compared	BI-CAR, AntHocNet, AODV, DSR

Table 3. Simulation Setting Parameters

5.2. Evaluation Metrics

To understand the performance of communication and safety, four important metrics were evaluated.

5.2.1. Packet Delivery Ratio (PDR)

The Packet Delivery Ratio measures the dependability of the data transmission and is expressed as the ratio between the number of packets that were delivered successfully to the number of packets that the sources created [21].

$$PDR = \frac{\text{Total Packets Received}}{\text{Total Packets Sent}} \times 100\% \quad (20)$$

A higher PDR, as expressed in Eq. (20), indicates greater stability in routing and resilience to link breakages. BI-CAR will be able to preserve the high PDR values because of its adaptive path selection based on the pheromone reinforcement and collision-risk filtering.

5.2.2. End-to-End Delay (E2E Delay)

This is a metric that is used to determine the average latency that a packet takes between the source and the destination. It considers all the potential delays in transmission, propagation, queuing and retransmission of each route.

$$E2E \text{ Delay} = \frac{1}{N} \sum_{i=1}^N (t_{receive}^{(i)} - t_{send}^{(i)}) \quad (21)$$

In Eq. (21), N is the total number of successfully received packets. This reflects communication latency. Lower delay values signify faster route convergence and efficient scheduling. BI-CAR minimizes delay by favoring links with lower CLC and stable CRI scores.

N in Eq. (21) is the overall number of packets that have been received successfully. This is a measure of communication latency. Smaller delay values are indicators of quick convergence of routes and effective scheduling. BI-CAR reduces delay in favor of links that have lower CLC and stable CRI scores.

5.2.3. Routing Overhead (ROH)

Routing Overhead expressed in Eq. (22) assesses protocol efficiency in maintaining topology information, calculated as the ratio of control packets (e.g., RREQ, RREP, ANT) to successfully delivered data packets.

$$ROH = \frac{\text{Total Control Packets}}{\text{Total Data Packets Received}} \quad (22)$$

Reduced ROH means that it is more scalable and efficient in control. Although BI-CAR proposes an update of pheromones and CRI, its localized reinforcement decreases network-wide floods, keeping its overhead moderate even in large scale.

5.2.4. Collision Avoidance Efficiency (CAE)

CAE evaluates the capability of the protocol to detect and prevent the likely mid-air UAV collisions. It is determined as the proportion of collision risks that have been avoided. The high CAE values show that the safety performance is higher during UAV operations.

CAE expressed in Eq. (23) is used to measure the capacity of the protocol to identify and avoid mid-air collisions, using the number of collision-risk events avoided.

$$CAE = \frac{\text{Number of avoided Collision Events}}{\text{Total Potential Collision Events}} \times 100\% \quad (23)$$

This is a safety-based measure that is exclusive to BI-CAR. It uses real-time calculation of DCPA (Distance at Closest Point of Approach) and TCPA (Time to Closest Point of Approach) to calculate the CRI and pre-emptive route changes may be made before physical interference takes place.

This evaluation was done with ten node densities (50-500). The four metrics above were calculated and averaged using ten simulation runs per density. The findings demonstrate that BI-CAR always had the highest PDR and CAE, as well as the lowest E2E delay, and had only average routing overhead. AntHocNet outperformed AODV and DSR in PDR and delay because of its ACO-based reinforcement, whereas it lacked the explicit collision-aware module of BI-CAR. The comparison graphs and detailed quantitative data are presented in the following section.

6. SIMULATION RESULTS

Relatively, the simulation outcomes in this section indicate the behavior of the proposed BI-CAR routing protocol with reference to AODV, DSR, and AntHocNet with different UAV densities of 50-500 nodes. The general results indicate that BI-CAR offers a superior performance regarding the delivery of packets, latency, safety efficiency, and routing stability, particularly in the condition of high-density and high-mobility FANET.

6.1. Packet Delivery Ratio (PDR %)

Figure 2 illustrates the Packet Delivery Ratio of various routing protocols as the x-axis with the number of drones as the y-axis. The findings reveal that BI-CAR always has a PDR of over 85 % when the network reaches a size of 500 nodes, which implies that it is effective in terms of managing congestion and high mobility. AntHocNet has a higher delivery rate than AODV and DSR due to its multipath routing which is based on pheromones but is still inferior to BI-CAR. BI-CAR has been shown to perform better than the other two because it is collision-aware when selecting links with the help of the Connectivity Risk Indicator (CRI) and its continuous reinforcement mechanism that can adjust to network conditions in real-time. Table 4 presents the respective values.

Table 4. Packet Delivery Ratio Values

Packet Delivery Ratio (PDR, %)				
Drones	BI-CAR	AntHocNet	AODV	DSR
50	96.80	93.50	89.40	87.80
100	94.70	90.20	85.60	83.20
150	93.10	88.40	82.90	80.50
200	91.60	86.10	80.30	78.20
250	90.40	84.30	78.50	76.90
300	89.30	82.50	76.10	74.40
350	88.10	81.70	75.00	73.30
400	87.30	79.80	73.60	71.50
450	86.50	78.90	72.40	70.20
500	85.20	77.40	71.30	69.10

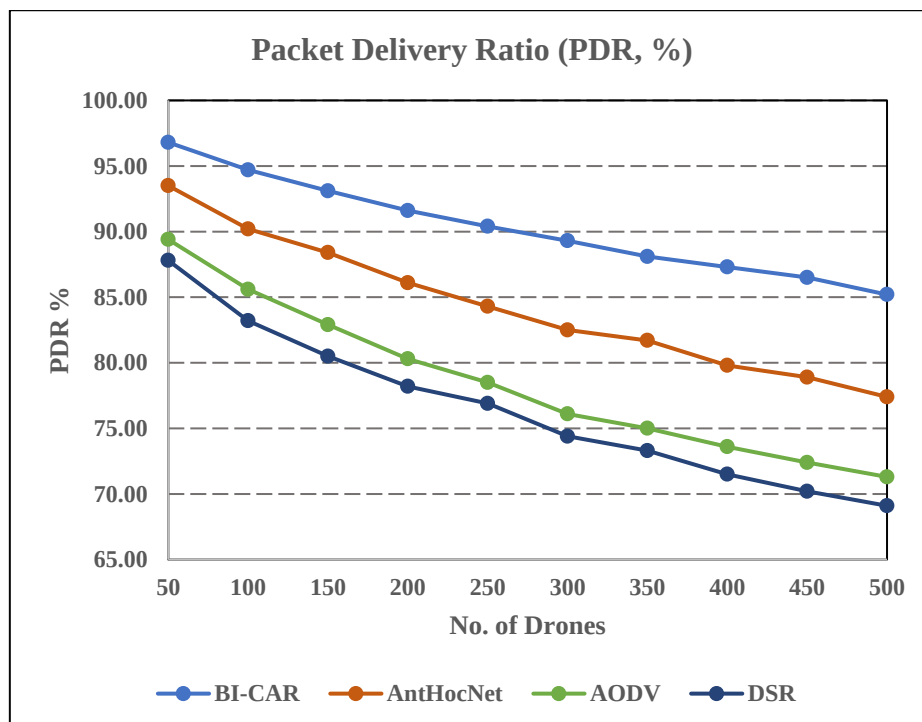


Figure 2 : Packet Delivery Ratio (PDR %)

6.2. End-to-End Delay (E2E Delay)

Figure 3 illustrates that the x-axis is the number of drones and the y-axis is the End-to-End Delay in milliseconds of the various routing protocols. The findings indicate that BI-CAR has the lowest average delay in all network sizes. The CLC driven route selection together with pheromone-based weighting allows it to forward data much faster and minimize queuing delays. Conversely, AODV and DSR exhibit a significant increase in delay as the number of nodes increases, due to frequent route discoveries and link failures. AntHocNet is superior to these two protocols, yet it still incurs moderate delays due to its periodic proactive exchanges of ants. Table 5 contains the corresponding values.

Table 5. End-to-End Delay

End-to-End Delay (ms)				
Drones	BI-CAR	AntHocNet	AODV	DSR
50	31.20	37.40	45.60	48.20
100	35.90	42.10	53.10	56.70
150	39.70	46.80	58.20	62.50
200	42.50	50.40	62.90	67.80
250	45.30	54.60	67.40	72.90
300	48.70	58.10	71.60	76.80
350	51.20	61.30	75.80	80.50
400	54.00	65.20	79.30	84.90
450	56.40	68.50	83.60	88.20
500	58.90	71.30	87.20	91.00

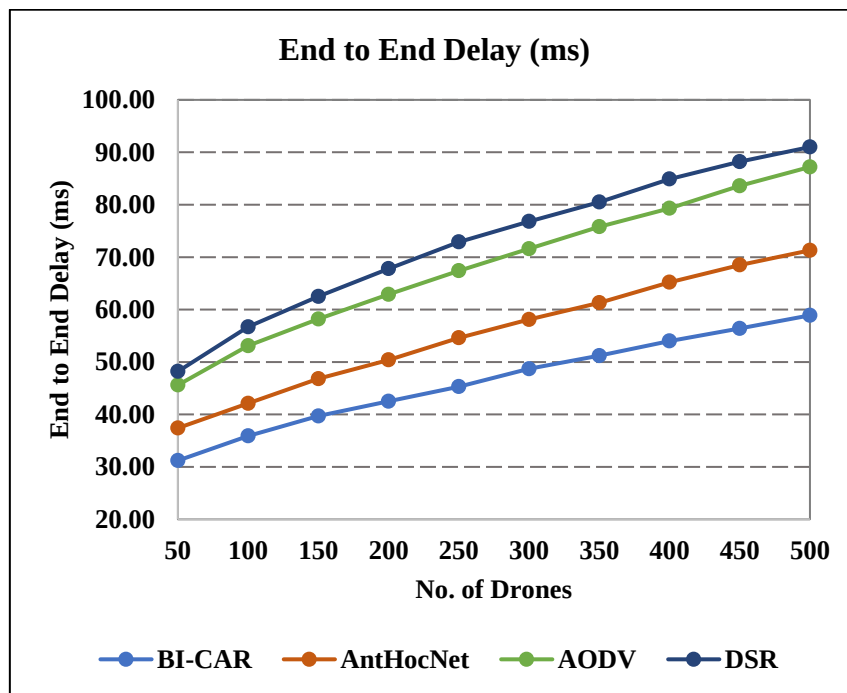


Figure 3 : End-to-End Delay (ms)

6.3. Routing Overhead (ROH)

Figure 4 demonstrates that the x-axis is the number of drones, and the y-axis is the Routing Overhead (ROH) of various routing protocols. The findings show that BI-CAR has a moderate level of overhead, despite the network being denser, increasing sub-linearly with the number of nodes. Even though AntHocNet uses pheromone-based reinforcement too, its periodic broadcasting of forward ants causes a slightly higher control traffic. On the contrary, AODV and DSR generate the largest routing overhead, because both protocols rely on full route rediscovery whenever a link failure happens. Table 6 summarizes the respective values.

Table 6. Routing Overhead

Routing Overhead				
Drones	BI-CAR	AntHocNet	AODV	DSR
50	0.12	0.15	0.21	0.19
100	0.17	0.20	0.29	0.27
150	0.21	0.24	0.33	0.31
200	0.24	0.27	0.36	0.34
250	0.26	0.29	0.39	0.36
300	0.28	0.31	0.42	0.38
350	0.30	0.33	0.43	0.39
400	0.31	0.35	0.44	0.40
450	0.33	0.36	0.45	0.42
500	0.34	0.37	0.46	0.43

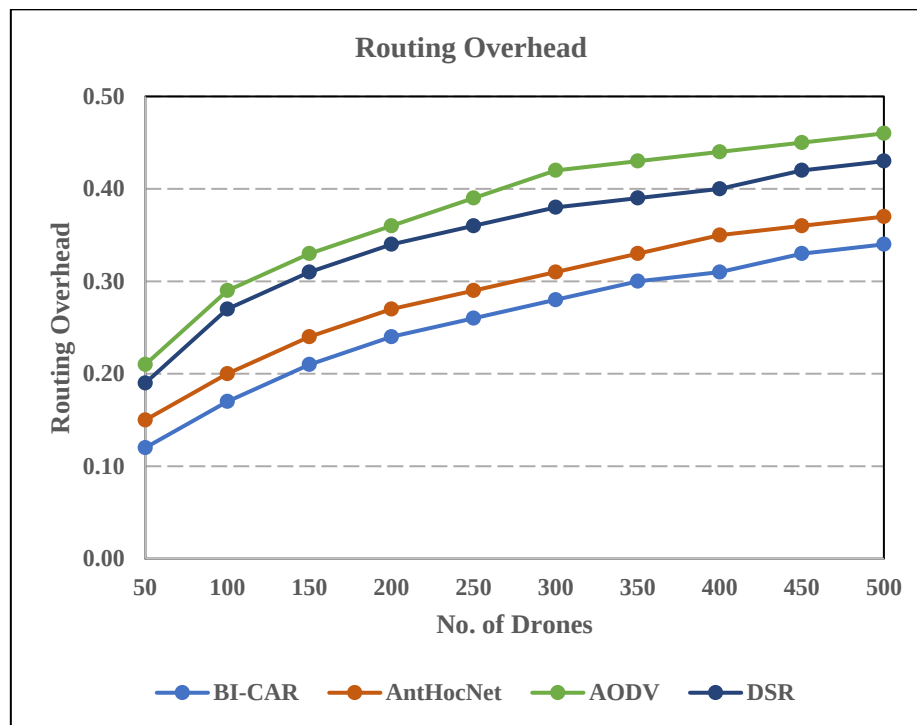


Figure 4 : Routing Overhead (ROH)

6.4. Collision Avoidance Efficiency (CAE)

Figure 5 illustrates the number of UAVs used as the x-axis and the Average Collision Avoidance Efficiency (CAE %) of the compared routing protocols as the y-axis. The findings show that BI-CAR has the best collision-avoidance efficiency among all the densities of UAVs with over 88% CAE at 500 nodes. This increase of 15-18% over AntHocNet and almost 25% over AODV and DSR is due to the CRI and the DCPA-TCPA predictive safety model. To maintain a safe distance during flight, BI-CAR monitors the movements of other UAVs and predicts potential crossing points, dynamically adjusting routing weights. AntHocNet, however, relies primarily on pheromone trails and reliability of the path disregarding the risk of spatial collision. There is also no risk estimation mechanism in 3D space in AODV and DSR, which increases the possibility of route conflicts and unsafe proximity in case of a dense network. Table 7 is the list of the corresponding values.

Table 7 Collision Avoidance Efficiency

Collision Avoidance Efficiency (CAE %)				
Drones	BI-CAR	AntHocNet	AODV	DSR
50	96.50	82.30	75.80	73.40
100	95.10	79.50	72.40	70.60
150	93.90	77.10	70.20	68.70
200	92.70	75.40	68.10	66.90
250	91.80	74.20	66.50	65.20
300	90.90	73.10	65.10	64.30
350	90.20	72.20	64.30	63.50
400	89.60	71.30	63.50	62.80
450	89.00	70.60	62.70	62.10
500	88.50	70.00	61.90	61.30

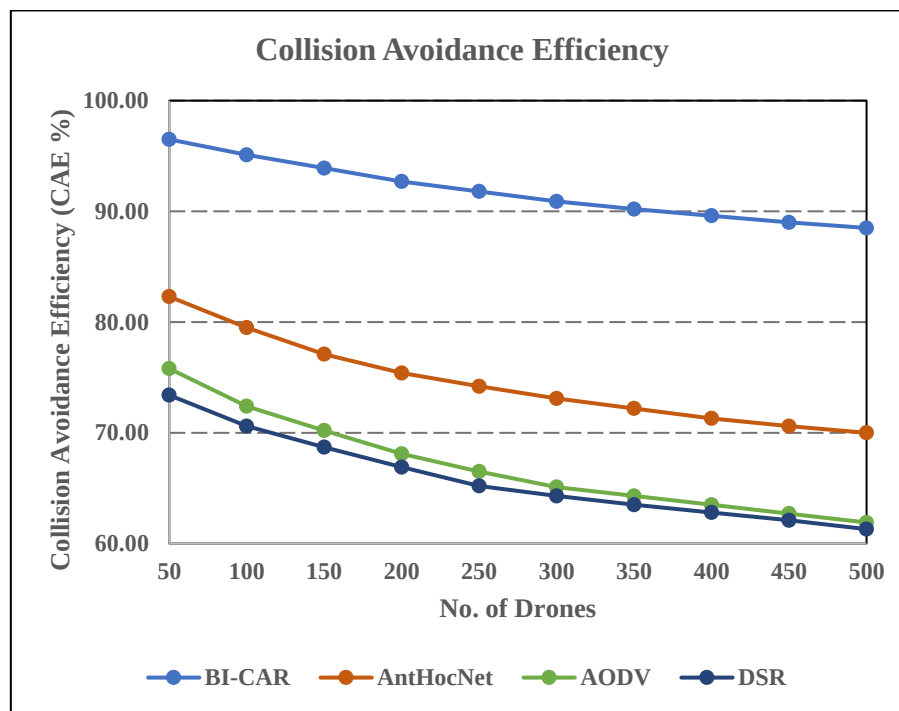


Figure 5 : Collision Avoidance Efficiency (CAE %)

6.5. Effectiveness Across Different Measures

Table 8 provides a comparative overview of each protocol's performance across the evaluated metrics. The simulation outcomes show that BI-CAR consistently outperforms AODV, DSR, and AntHocNet under all tested conditions. This improvement is due to BI-CAR's hybrid routing mechanism, which combines probabilistic pheromone-based path selection, CRI-based collision prediction, and composite link-cost evaluation. Together, these features ensure a strong balance between communication reliability and airspace safety. Even as the number of UAVs increases, BI-CAR sustains higher data delivery rates and lower latency while keeping routing overhead within acceptable limits. Its adaptive reinforcement process and localized recovery mechanism further enhance stability, making BI-CAR particularly effective for large-scale, dynamic aerial networks.

Metric	BI-CAR	AntHocNet	AODV	DSR
Packet Delivery Ratio (PDR)	High (> 85 % up to 500 UAVs); stable under dense traffic	Good ($\approx$ 78 – 93 %)	Degrades rapidly beyond 300 nodes	Similar decline to AODV
End-to-End Delay	Lowest; increases moderately with node count	Moderate; higher due to proactive ants	High; frequent rediscovery	Highest; stale cache issues
Routing Overhead	Low-to-moderate; local reinforcement only	Moderate; periodic ant generation	High; full rediscovery floods	Moderate-high; cache maintenance
Collision Avoidance Efficiency	Excellent (> 89 %); proactive safety model	Low-moderate (no CRI)	Poor (no collision awareness)	Poor (no 3D safety layer)

Table 8 : Overview of Simulation Results for Evaluation Metrics

7. RESULTS ANALYSIS AND DISCUSSION

The total and the relative analysis verify that BI-CAR is always better than AODV, DSR, and AntHocNet in all the scales of the network. The most interesting fact is that it is more accentuated with the increase in node density and mobility and its flexibility to dynamic FANET conditions.

It collaboratively reduces retransmissions and route rediscoveries of its composite link-cost model and risk-adaptive route selection of BI-CAR stem. BI-CAR is proactive in keeping the routes stable by reinforcing with pheromones and evaluating the links by CRI, as opposed to the reactive schemes that re-establish routes when they fail.

The routing overhead is a little bit more than the reactive protocols only, due to the sub-linear dependence on network size of the efficient maintenance of pheromones. The efficiency of collision avoidance that is above 88% indicates the capability of BI-CAR to resolve spatial conflicts by predicting and avoiding them using DCPA-TCPA-based trajectory analysis- a feature that is not present in the benchmark schemes.

All in all, based on the facts, BI-CAR strikes a fair compromise among communication reliability, latency, and aerial safety. The findings affirm the fact that bio-inspired learning and predictive modeling can be significantly enhanced to enhance the routing resilience in large-scale and high-mobility UAV networks.

8. CONCLUSION

In this paper, the bio-inspired collision-aware routing protocol to FANETs was proposed as BI-CAR, which integrates the CRI calculation, composite link-cost estimation, and pheromone-based reinforcement to provide reliable and safe data delivery. Based on the simulation, it concludes that BI-CAR has a higher packet delivery, reduced delay, and high collision-avoidance efficiency than AODV, DSR, and AntHocNet. It established a robust trade-off between the performance of communication and airspace safety through the decentralized decision-making and route maintenance. The further work may be dedicated to BI-CAR to energy-conscious optimization and experimental validation of multi-UAV testbed under the real world in order to determine the scalability and effectiveness of practical deployment under heterogeneous flight conditions.

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