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Resilient Artificial Bee Colony Optimized AODV Routing Protocol (RABCO-AODV-RP) for Minimizing the Energy Consumption in Flying Ad-Hoc Network

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Abstract – Flying Ad-Hoc Networks (FANETs) have gained prominence in various applications, ranging from surveillance to disaster response. Their dynamic and resource-constrained nature makes efficient energy utilization a paramount concern. One significant challenge in FANETs is minimizing energy consumption, which is essential for prolonging the network lifetime and ensuring continuous operation. This paper introduces the Resilient Artificial Bee Colony Optimized AODV Routing Protocol (RABCO-AODV-RP) to address this challenge. RABCO-AODV-RP leverages the Artificial Bee Colony optimization algorithm to enhance AODV routing, optimizing route selection to minimize energy consumption while maintaining network resilience. The working mechanism of RABCO-AODV-RP encompasses two primary phases: route discovery and route maintenance. During route discovery, the protocol intelligently selects energy-efficient paths using the optimization algorithm, reducing energy waste. In the route maintenance phase, RABCO-AODV-RP continuously adapts to network dynamics, updating routes to ensure efficient and resilient communication. Extensive simulations were conducted using the NS3 network simulator to assess its performance using packet delivery ratio, packet drop ratio, throughput, end-to-end delay, energy consumption and hop count as performance metrics. The results and discussions indicate that RABCO-AODV-RP outperforms traditional AODV routing protocol. It improves packet delivery, throughput and reduces packet drop ratio, end-to-end delay and hop count. This research underscores the potential of RABCO-AODV-RP as a promising solution for extending the operational lifetime of FANETs and ensuring reliable communication in demanding environments.

Index Terms – UAV, ABC, AODV, Optimization, FANET, Routing, Energy.

1. INTRODUCTION

FANET represents a paradigm shift in wireless communication and network deployment by leveraging the dynamic capabilities of unmanned aerial vehicles (UAVs), commonly called drones[1]. FANETs have gained considerable attention due to their potential to provide on-demand and rapidly deployable communication infrastructure in scenarios where traditional networks may be absent, compromised, or inadequate. These networks hold promise in various applications, including disaster response, search and rescue missions, military operations, environmental monitoring, and even revolutionizing precision agriculture practices[2].FANETs overcome the limitations of terrestrial communication infrastructure, allowing for communication and data sharing over challenging terrains, remote regions, or during emergencies. The inherent mobility of UAVs enables FANETs to cover large geographical areas and dynamically adapt to changing environments. In disaster-stricken areas where ground-based infrastructure is destroyed, FANETs can be rapidly deployed to establish communication links, facilitating coordination among first responders and aiding relief efforts[3].

FANETs offer enhanced situational awareness for military operations by providing real-time communication and surveillance capabilities in contested or hard-to-reach areas. These networks can facilitate data exchange between ground forces, airborne assets, and command centers, improving tactical decision-making and coordination[4].FANETs hold the potential to revolutionize the way farmers monitor and

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manage their fields. Equipped with various sensors, drones in FANETs can collect data on crop health, soil moisture, pest infestations, and other critical parameters. This data can then be transmitted to central systems for analysis, enabling farmers to make timely and informed decisions regarding irrigation, fertilization, and disease control.

The Key Features of FANET include:

- Mobility and Coverage: UAVs' mobility enables FANETs to cover large and remote areas, making them particularly valuable in scenarios with sparse or nonexistent communication infrastructure.
- Rapid Deployment: FANETs can be swiftly deployed in emergencies, providing communication and data-sharing capabilities in disaster-stricken regions where traditional networks are compromised.
- Dynamic Network Topology: The adaptable nature of FANETs allows the network topology to change in response to evolving communication needs, making them suitable for scenarios with unpredictable dynamics.
- Data Collection and Relay: Drones within FANETs can serve as data collectors and relays, retrieving information from ground-based sensors or other devices and transmitting it to designated destinations.

The heart of any network lies in its routing mechanism, and FANET is no exception. Routing in FANET involves determining the optimal paths for data transmission among drones and other network nodes[5]. However, the dynamic nature of UAVs introduces unique challenges to the routing process. Due to signal interference and battery constraints, drones are subject to erratic movements, altitude changes, and communication disruptions. These challenges make the development of efficient and reliable routing algorithms in FANET a non-trivial task[6].

Bio-inspired optimization (BIO) is a captivating computational approach that has captivated researchers across disciplines by mimicking the complex and effective strategies found in the natural world[7]. This paradigm leverages biological systems' remarkable efficiency, adaptability, and problem-solving capabilities over billions of years of evolution[8]. By translating these mechanisms into computational algorithms, BIO offers innovative and often highly efficient solutions to complex optimization and decision-making challenges[9].

1.1. Problem Statement

The core challenge in FANETs lies in mitigating the excessive energy consumption inherent to their operation. FANETs are characterized by mobility, limited onboard power sources, and a pressing need for prolonged network longevity. The energy-related issues are exacerbated by the lightweight and energy-efficient hardware requirements specific to flying platforms, such as drones or UAVs. These networks often operate in remote or hard-to-reach locations, challenging energy replenishment. FANETs confront dynamic and unpredictable environmental conditions, necessitating frequent route updates and network reconfigurations, which introduce additional energy overhead. FANETs are frequently tasked with supporting bandwidth-intensive applications like video streaming and high-resolution image capture, further straining their already constrained energy resources. Addressing these energy consumption challenges is vital for ensuring the sustainability and efficacy of FANETs. Developing innovative and efficient solutions to optimize energy usage while maintaining reliable communication in dynamic and resource-limited settings is paramount in this context.

1.2. Motivation

The motivation for this research arises from the critical need to address energy consumption issues in FANETs. FANETs have gained prominence in various applications, but their energy efficiency challenges pose significant concerns. The operation of drones and unmanned aerial vehicles (UAVs) in FANETs relies on limited onboard power sources, making energy optimization crucial. Prolonging mission durations, reducing the environmental impact, and cutting operational costs are imperative objectives. The dynamic and unpredictable nature of FANETs necessitates adaptable routing strategies to maintain communication reliability. Therefore, addressing energy efficiency in FANETs has become a pressing concern. This research seeks to contribute to developing solutions that enhance energy efficiency in FANETs, ensuring their sustainability and effectiveness in diverse applications.

1.3. Objective

This work aims to develop and assess the Resilient Artificial Bee Colony Optimized AODV Routing Protocol (RABCO-AODV-RP) in the context of FANETs. The primary goals involved in this research are as follows:

- Algorithm Integration and Enhancement: This work focuses on seamlessly integrating the Artificial Bee Colony optimization algorithm into the AODV routing protocol to enhance energy efficiency and adaptability.
- Energy-Efficient Route Discovery: The primary objective is to optimize the route discovery phase by employing the artificial bee colony algorithm to intelligently select energy-efficient paths during the route establishment process.
- Resilience to Network Dynamics: This research strives to ensure the proposed RABCO-AODV-RP can effectively adapt to the dynamic conditions encountered in FANETs,

maintaining reliable communication by continuously monitoring and adjusting routes as needed.

1.4. Organization of the Paper

The significant goal of this work is to provide a efficient solution to address energy consumption challenges in FANETs, ensuring the sustainability and reliability of these networks in dynamic and resource-constrained environments. The rest of this paper is organised as follows: Section 2 discusses the literature review, Section 3 proposes the RABCO-AODV-RP routing protocol for FANET. Section 4 analyses the simulation settings and performance metrics for this research work. Section 5 concludes this work.

2. LITERATURE REVIEW

"Prediction-Supported Adaptive Routing (PAR)" [10] introduces an innovative routing protocol for FANETs that utilizes deep reinforcement learning. It is designed to predict and adapt to the dynamic network conditions often encountered in aerial environments. By leveraging advanced machine learning techniques, this protocol enhances the reliability and efficiency of communication within FANETs. "Adaptive Routing with GAN Imitation (AR-GAIL)" [11] offers an adaptive routing protocol for FANETs that employs Generative Adversarial Imitation Learning (GAIL). This approach enables FANETs to learn from imitation, allowing them to adapt their routing strategies based on observed network behavior. AR-GAIL's key innovation lies in its ability to continuously improve routing decisions through imitation, making it well-suited for scenarios with evolving network dynamics. "Q-FANET" [12]enhances routing in FANETs by employing an improved Q-learning-based protocol. Q-learning is a reinforcement learning technique that helps FANET nodes make informed routing decisions by considering their past experiences. The protocol's advancements aim to optimize communication and routing decisions, making it especially effective in dynamic network conditions.

"Red Deer Clustering-Based Routing"[13]introduces a routing protocol inspired by the red deer optimization algorithm. The protocol focuses on creating reliable data dissemination strategies in FANETs, where nodes can organize themselves into efficient data-sharing clusters. By mimicking the behavior of red deer in forming social clusters, this protocol contributes to enhanced data reliability and network performance within FANETs. "Distributed Priority Tree Routing (DPTR)" [14] is a distributed priority tree-based routing protocol designed explicitly for FANETs. It introduces a hierarchical and structured approach to routing, where nodes form priority trees to facilitate more organized and efficient communication. This innovative protocol enhances network organization and routing efficiency in FANETs, making it well-suited for scenarios involving aerial ad-hoc networks with a distributed architecture. "Interference-Aware Multi-UAV Routing"[15]addresses the challenge of interference in multi-UAV FANETs by developing a comprehensive solution that optimizes power control and routing. By considering these two aspects jointly, the protocol minimizes interference, enhances communication reliability, and optimizes network performance. This is a significant advancement in FANETs, where interference can significantly affect the quality of communication and data transmission.

"OLSR+: Fuzzy Logic Routing" [16] introduces a novel routing approach based on fuzzy logic for FANETs. Fuzzy logic makes routing decisions more adaptable and context-aware, improving network efficiency and adaptability in dynamic aerial scenarios. This contribution advances the routing field in FANETs by incorporating fuzzy logic for better decision-making. "MWCRSF: Mobility-Based Cluster Routing" [17] presents a Mobility-Based Weighted Cluster Routing Scheme designed to improve the efficiency of FANETs. By considering the mobility of nodes, this scheme optimizes the formation of clusters, leading to more efficient and organized data communication. The essential contribution lies in utilizing mobility-based clustering techniques to enhance network performance. "Resource Allocation with Anypath Routing" [18] focuses on resource allocation in FANETs for dataflow applications using anypath routing. It optimizes the allocation of resources, such as bandwidth and processing power, to maximize dataflow application performance. The essential contribution is developing an effective resource allocation strategy tailored to the specific requirements of FANET dataflow applications.

"Trajectory-Based Routing" [19] introduces a cyber-physical routing protocol that exploits the trajectory dynamics of UAVs to improve mission-oriented FANET. By leveraging trajectory information, the protocol optimizes routing decisions, considering the specific goals and dynamics of mission-oriented FANETs. This contribution is crucial for achieving mission success in such networks. "Hopfield Neural Network Optimized Routing"[20]emphasizes the increasing importance of FANETs in various industries and recognizes the specific challenge of routing in FANETs, particularly the high-speed mobility of nodes. It introduces an innovative approach that combines the Dynamic Source Routing (DSR) protocol with the continuous Hopfield neural network to optimize routing in response to the rapid movements of FANET nodes. "E-AntHocNEt" [21] introduces a specialized routing protocol for FANETs, addressing their distinct challenges and operational needs. Leveraging Ant Colony Optimization (ACO), a robust metaheuristic, enhances the path selection and offers a dependable and efficient routing approach. By incorporating an energy-stabilizing parameter, the protocol optimizes energy consumption, which is crucial for UAVs' extended operation and mission success.

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Table 1 highlights the summarized view of the methodology, advantages and disadvantages of the research work in the literature.

Table 1 Comparison of State-of-the-Art Methodologies

State of the art methodology	Problem Identified	Solution	Strength	Weakness
Prediction-Supported Adaptive Routing (PAR) [10]	To find the optimal routing path between source and destination nodes	Mobility prediction algorithm using deep learning for location estimation	On-demand broadcasting of Hello packets reduces routing overhead	Increases computational complexity
Adaptive Routing with GAN Imitation (AR-GAIL) [11]	To improve adaptability to network dynamics	Routing protocol designed based on generative adversarial imitation learning	Minimal end-to-end delay	Learning routing policies and updating look-up tables degrades the performance
Q-FANET [12]	To reduce the network delay and improve performance	Improved Q-Learning algorithm	Low delay and jitter	Energy consumption issue is not addressed
Red Deer Clustering-Based Routing [13]	To provide a comprehensive review of bio-inspired algorithms suitable for FANET environment	Taxonomy of metaeurisitic optimization based routing is presented	Algorithms under different categories are covered	Detailed approach for the different categories of routing protocols are not discussed
Distributed Priority Tree Routing (DPTR) [14]	Designing a routing protocol for a partitioned network	Distributed priority-tree based routing protocol is designed	The proposed protocol provides the network functionality for the partitioned networks	Aerial to ground network coordination process handled using the framework is complex
Interference-Aware Multi-UAV Routing [15]	To maximise network throughput with the allocated power	An optimization problem(NP-hard) is formulated and solved	A near-optimal solution is obtained for throughout maximisation	Increase in computational complexity during optimal path selection
OLSR+: Fuzzy Logic Routing" [16]	To improve the OLSR routing protocol for estimating link lifetime	Multipoint relay nodes are selected using fuzzy mechanism	Better performance in terms of delay and throughput	More routing overhead when compared to bench mark routing protocols
MWCRSF: Mobility-Based Cluster Routing [17]	To design an optimised routing scheme with the constrained network resources	Mobility based weighted cluster routing scheme is proposed	Improved cluster head selection and next hop routing	Setting up of initial UAV clusters takes a longer time
Resource	To improve the quality of	Anypath-based	Achieves quality	As transmission

Allocation with Anypath Routing [18]	communication between nano-services	heuristic algorithm is proposed for resource allocation	in communication through a virtual network embedding framework	rate increases, the loss probability also increases
Trajectory-Based Routing [19]	To create a routing protocol which exploits the native trajectory dynamics of FANET	A mathematical model is constructed for flying process	High packet delivery ratio is achieved	The network jittter is to be reduced
Hopfield Neural Network Optimized Routing [20]	To improve stability and communication efficiency of network	DSR routing protocol is optimised using continuous Hopfield neural network	The proposed protocol is more stable and has a lower probability of route failure	As speed increases, the packet delivery ratio decreases
E-AntHocNEt" [21]	To create a nature inspired energy efficient routing protocol to improve network performance	Modified AntHocNet is used for routing protocol	Network throughput and packet received ratio are high when compared to legacy routing protocols	Performance of routing protocol using different mobility models are to be incorporated

The literature survey discussed so far analyses the routing protocols from various aspects but they lack an in-depth analysis of energy efficiency. Till now energy efficiency is not well explored. This research work unfolds this research gap and proposes the RABCO-AODV-RP routing protocol for energy efficiency in FANET.

3. RESILIENT ARTIFICIAL BEE COLONY OPTIMIZED AODV ROUTING PROTOCOL

Routing protocols play a significant role in FANETs as they determine the packet delivery ratio, energy consumption of nodes in the network, and other related factors. This paper uses an ad-hoc on-demand distance vector (AODV) routing protocol with link failure prediction for route discovery. The AODV protocol uses the hop count parameter to determine the shortest path. To construct the best route, this parameter alone is not sufficient. Hence, an optimization approach is necessary to further improve the quality of the route.

In the literature, many researchers showed interest in bio-inspired, swarm-based optimization strategies to establish an efficient route for communication among the flying nodes. The Artificial Bee Colony (ABC) optimization algorithm is one of the practical approaches in establishing the routes to initialize the communication and to find the best route to obtain a solution. The flying ad-hoc nodes can be compared with the honey bees in the hive. The collaborative behaviour of bees can be applied in the FANET environment so that the flying nodes communicate with each other to exchange path information to effectively deliver resources. The following sections describe the AODV routing protocol, the traditional ABC algorithm and the proposed RABCO-AODV-RP algorithm.

3.1. Optimized Approach to Improve AODV Routing Protocol

AODV is a reactive routing protocol that establishes the route between the source and destination nodes only when packets are to be delivered. This protocol is well suited for the FANET environment as it works well when the mobility of nodes is high. The protocol involves two main phases, namely route discovery and route maintenance. During the route discovery phase, the sender broadcasts a route request (RREQ) message. If a node receives this message, it checks its routing table to know whether there is any route for the destination. If the route is not found, the hop count field is incremented, the time-to-live field is decremented, and the message is passed to the neighbouring node. The neighbouring node checks its routing table; this process is repeated if the destination is not found. If the destination is found or a node containing a route to the destination is found, it sends a route reply (RREP) message to the source through the reverse route. Upon receiving the RREP message, the source node selects the route with minimum hop count for data transmission. Once the data transmission begins, the nodes in that route update the timer, which is when the transmission occurs.

During the route maintenance, the protocol ensures the entire network is connected. Network nodes must connect to their neighbours for a specific period to ensure this. This connection helps the nodes to know their active neighbours.

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The AODV protocol sends a hello message to check for the connectivity of neighbourhood nodes and updates their routing table. If new hello messages, data transmission or control messages are not received, there may be link failures in the nodes.

If any such link failure in the route is detected, a route error (RERR) message is sent to the source and all active nodes in that route so that the source node starts the route discovery process again, and the active nodes in the network update their routing table.

The problem with this approach is that the link failure results in the degradation of the entire network due to packet loss and routing overhead. If the possibility of a link failure can be detected in advance, the routing performance of the network will be improved. This link failure prediction is done in the proposed system based on the signal strength received by the packets.

A threshold value of received signal strength is calculated. If the received signal strength is below the threshold value, it is intimated to the source node before the actual failure so that it can search for an alternate path even before the actual link failure occurs.

In the proposed method, link failure prediction is estimated using Newton's Divided Difference Interpolation Formula, which is shown in Eq. (1):

$$P_n(X) = a_0 + a_1(X - X_0) + a_2(X - X_0)(X - X_1) + \cdots + a_n(X - X_0)(X - X_1)\ldots(X - X_{n-1}) \quad (1)$$

The following are the assumptions made during the link failure prediction process:

- RSS_1, RSS_2, RSS_3 - the signal strengths of three consecutive data packets from their predecessor nodes.
- t_1, t_2, t_3 - the time instances at which the data packets have arrived.
- RSS_t - Threshold value of received signal strength at time t_p
- t_p - Predicted time during which the received signal strength falls below RSS_t
- Δ_1, Δ_2 - First and second divided differences

The threshold value of the received signal strength RSS_t is calculated using Eq. (2).

$$\mathrm{RSS_t} = \mathrm{RSS_1} + (\mathrm{t_p} - \mathrm{t_1})\Delta_1 + (\mathrm{t_p} - \mathrm{t_1})(\mathrm{t_p} - \mathrm{t_2})\Delta_2 \quad (2)$$

By substituting the first and second differences, Eq. (3) is derived.

$$\mathrm{RSS_t} = \mathrm{RSS_1} + \frac{(\mathrm{t_p}-\mathrm{t_1})(\mathrm{RSS_2}-\mathrm{RSS_1})}{(\mathrm{t_2}-\mathrm{t_1})} + (\mathrm{t_p} - \mathrm{t_1})(\mathrm{t_p} - \mathrm{t_2})\left(\frac{(\mathrm{RSS_3}-\mathrm{RSS_2})}{(\mathrm{t_3}-\mathrm{t_2})} - \frac{(\mathrm{RSS_2}-\mathrm{RSS_1})}{(\mathrm{t_2}-\mathrm{t_1})}\right)/(\mathrm{t_3} - \mathrm{t_1}) \quad (3)$$

Calculate X and Y as shown in the Eq. (4) and Eq. (5)

$$\mathrm{X} = \left(\frac{\mathrm{RSS_2}-\mathrm{RSS_1}}{\mathrm{t_2}-\mathrm{t_1}}\right) \quad (4)$$

$$\mathrm{Y} = \left(\frac{(\mathrm{RSS_3}-\mathrm{RSS_2})}{(\mathrm{t_3}-\mathrm{t_2})} - \frac{(\mathrm{RSS_2}-\mathrm{RSS_1})}{(\mathrm{t_2}-\mathrm{t_1})}\right)/(\mathrm{t_3} - \mathrm{t_1}) \quad (5)$$

Then Eq. (3) can be written as shown in Eq. (6).

$$\mathrm{RSS_t} = \mathrm{RSS_1} + (\mathrm{t_p} - \mathrm{t_1})\mathrm{X} + (\mathrm{t_p} - \mathrm{t_1})(\mathrm{t_p} - \mathrm{t_2})\mathrm{Y} \quad (6)$$

Eq. (6) can be written as

$$\mathrm{Yt_p^2} + (\mathrm{X} - \mathrm{Yt_1} - \mathrm{Yt_2})\mathrm{t_p} + (\mathrm{RSS_1} - \mathrm{RSS_t} - \mathrm{Xt_1} + \mathrm{t_1t_2Y}) = 0 \quad (7)$$

Eq. (7) is of the form shown in Eq. (8).

$$\mathrm{xt_p^2} + \mathrm{yt_p} + \mathrm{z} = 0 \quad (8)$$

where $x = Y, y = (X - Yt_1 - Yt_2)$, z= $(RSS_1 - RSS_t - Xt_1 + t_1t_2Y)$

Thus, the link failure prediction at the time t_p can be expressed as in Eq. (9)

$$\mathrm{t_p} = \frac{-\mathrm{y}+\sqrt{\mathrm{y}^2-4\mathrm{xz}}}{2\mathrm{x}} \quad (9)$$

Apart from the link failure prediction time t_p, the protocol requires another time parameter t_c which sends an error message to the source node so that it can find an alternate route either by local route repair method or finding a new path upon expected link failure. The pseudo-code of optimized AODV routing protocol with link failure prediction is provided in Algorithm 1.

Step 1:	For every neighbor node, when a data packet arrives, update the received signal strength(RSS_1, RSS_2, RSS_3) at time instances (t_1, t_2, t_3)
Step 2:	If ($RSS_1 > RSS_2$) and ($RSS_2 > RSS_3$) then
Step 3:	Calculate $t_p and\ t_c$
Step 4:	if (current time $\geq t_c$) then
Step 5:	Send the expected link failure message
Step 6:	If local route repair is possible, reroute the packets through this route or find a new route.
Step 7:	Send the data packets through the new route
Step 8:	Send a message to the source node to find the shortest path.

Algorithm 1 Optimized AODV with Link Failure Prediction Algorithm

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3.2. Traditional ABC Algorithm

ABC algorithm is based on the swarm intelligence of honey bees in the hive. A population-based algorithm finds the best solution from all feasible solutions. In a bee colony, there are three types of bees: employed bees, onlooker bees, and scout bees. Employed bees are responsible for finding food sources containing nectar. After employed bees find the possible food sources, they exchange the information about food sources with the onlooker bees. Depending on the food sources the employed bees provide, the onlooker bees start examining further food sources to arrive at paths containing reasonable nectar amounts. This process is iterated for a specific predetermined limit. When the onlooker bees cannot further improve the food source, they abandon that poor path and become scout bees. The scout bees search for food sources randomly, and the entire process is repeated based on the maximum cycle number. The ABC algorithm can be outlined as follows:

Step 1: Initialization Phase

Step 2: Repeat.

- Employed Bees Phase to collect possible food sources.
- Onlookers Bees Phase to evaluate the nectar amount of food sources.
- Scout Bees Phase to explore new food sources and to retain good sources found so far.

Step 3: Until control parameters satisfy the requirement.

Algorithm 2 ABC Algorithm

The algorithm defines three control parameters: Population size(S), Maximum Cycle Number, and limit. These parameters are to be predetermined by the user. The expanded version of the ABC algorithm is described as follows:

3.3. Enhanced Artificial Bee Colony Algorithm (RABCO-AODV-RP)

Recent research on the traditional ABC algorithm proved that it suffers from premature convergence, poor exploitation, and high perturbation. The following enhancements have been made to the traditional algorithm to overcome these issues.

3.3.1. Initialization Phase

In this phase, an initial set of solutions is randomly generated by employed bees in the search space $[P_{min,j},\ P_{max,j}]$by using the Eq. (10):

$$P_{ij} = P_{min,j} + rand(0,1)([P_{max,j} - P_{min,j}]) \qquad (10)$$

where P_{ij} is the j_{th} dimension of the i_{th} solution, $P_{min,j}$ is the lower bound of the solution, $P_{max,j}$ is the upper bound of solution and rand(0,1) is a random number in the range [0,1]

3.3.2. Employed Bees Phase

This phase builds new solutions for every solution provided by the initialization phase using Eq. (11). The fitness of the new solutions is calculated and compared with that of the initial solutions. If the fitness of the new solution is better than the initial one, the new solution replaces the initial solution and is saved in memory. Otherwise, the initial solution is retained, and a counter value is incremented to abandon the poor solution in the final phase.

$$Q_{ij} = P_{ij} + \emptyset \times rand[-1,1] \times (P_{ij} - P_{kj}) \qquad (11)$$

where P_{ij} is the j^{th} dimension of the current solution considered, and i denotes the solution from the population space. Q_{ij} is the j^{th} dimension of the new solution $\emptyset$ is a randomly determined value within the range [-1,1], P_{kj} is the j^{th}dimension of another solution selected randomly from the population space, and k denotes the dimension of that solution such that $P_i \neq P_k$.

3.3.3. Onlooker Bees Phase

In this phase, all the food sources given by the employed bees phase are evaluated, and a roulette wheel selection scheme is involved in selecting the best food source, which is based on the probability value of the fitness function as in Eq. (12):

$$prob_i = \frac{f(P_i)}{\sum_{i=1}^{N} f(P_i)} \qquad (12)$$

where $prob_i$ is the probability of the solution for the i_{th} iteration, $f(P_i)$is the fitness value of the i_{th} iteration.

The fitness of the solution is calculated using Eq. (13)

$$f(P_i) = \begin{cases} \frac{1}{1+f(P_i)}, & iff(P_i) \geq 0 \\ 1 + |f(P_i)|, & iff(P_i) < 0 \end{cases} \qquad (13)$$

3.3.4. Scout Bees Phase

This phase checks for improving the food source through a control parameter *limit*. If the food source cannot be improved even after the parameter *limit* is reached, it is assumed that it is abandoned. The employee bee of this abandoned food source becomes the scout bee, and it starts generating new solutions based on Eq. (10).

3.3.5. Logistic Chaotic Map

The traditional ABC algorithm generates a randomly distributed initial solution. This random distribution does not guarantee ergodicity and diversity. Ergodicity ensures that the samples drawn represent the entire population's properties. Since the initial solutions of the algorithm are not ergodic, there is a possibility that the candidate solutions may fall into the local optimum. This may slow down the convergence speed also. Hence, the RABCO-AODV-RP algorithm uses chaotic maps by replacing the random initialization

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procedure. A chaotic map is a deterministic mathematical function that produces arbitrary values highly dependent on the initial conditions. There are different types of chaotic maps: Circle, Cubic, Guass, ICMIC, Logistic, Sinusoidal, and Tent Map. The RABCO-AODV-RP algorithm uses a one-dimensional Logistic chaotic map due to its simplicity and efficiency in generating initial candidate solutions. A logistic chaotic map can be mathematically defined in Eq.(14).

$$x_{k+1} = ax_k(1 - x_k) \quad (14)$$

where 'x' represents the population at any given time, 'k' and 'a' represent the growth rate. This map generates chaotic sequences in (0, 1). The selection of the growth rate parameter value is significant. A deficient growth rate value may result in the population's extinction, and a very high growth rate may settle down with a constant value. Setting $a = 4$ produces a perfect logistic map for random number generation. The initial iterations of the logistic chaotic map are represented as Eq.(15) - Eq.(17):

$$x_1 = ax_0(1 - x_0) \quad (15)$$

$$x_2 = a^2(1 - x_0)x_0(1 - ax_0 + ax_0^2) \quad (16)$$

$$x_3 = a^3(1 - x_0)x_0(1 - ax_0 + ax_0^2) \times (1 - a^2x_0 + a^2x_0^2 + a^3x_0^2 - 2a^3x_0^3 + a^3x_0^4) \quad (17)$$

The solution generated by the logistic map depends on the growth rate 'a'. The exact solution for any given function $f(x)$ is of the form shown in Eq. (18):

$$x_n = \frac{1}{2}(1 - f(x)[a^n f^{-1}(x)(1 - 2x_0]) \quad (18)$$

The exact solutions are available only in a few cases. When the growth rate is $0 \leq a \leq 1$, the logistic map offers the solution in closed form as in Eq. (19)

$$x_n \leq \frac{x_0}{a^{-n} + x_0 n} \quad (19)$$

The solution for the case when a=4 is given in Eq.(20)

$$x_n = \sin^2(2^n \mu\pi) \quad (20)$$

where μ is the initial parameter, which is calculated using Eq.(21)

$$\mu = \frac{1}{\pi}\sin^{-1}\sqrt{x_0} \quad (21)$$

3.3.6. Simulated Annealing-Based Search

Employed bees are responsible for finding new solutions from the search space. The traditional ABC algorithm applies a greedy selection strategy between the new food source and a random neighbour food source. This process may fall into local optima. The greedy selection strategy is replaced with simulated annealing to maintain population diversity. Simulated annealing is a probabilistic technique used in meta-heuristic optimization problems to find the global minimum of an objective function. The initial solution is represented as $s \in N$ where N is the set of all possible solutions. The initial temperature must be set to calculate the energy of the initial candidate solution. From the initial solution, new candidate solutions are defined by including a perturbation function. The energy difference between the new and current solutions determines the acceptance criterion based on Boltzmann probability distribution. The perturbation function and acceptance criterion are applied to the current solution to get a better solution. The acceptance criterion is called the Metropolis Acceptance Criterion and is represented as Eq.(22):

$$P(\Delta E) = \begin{cases} e^{\frac{-\Delta E}{t}}, & \Delta E > 0 \\ 1, & \Delta E \leq 0 \end{cases} \quad (22)$$

Here, the energy E can be regarded as the fitness function. This probability of accepting a new solution involves accepting some worse solutions when the temperature T is at the maximum. When the temperature is gradually reduced, the system accepts only the optimal solution, avoiding falling into local optima and moving towards global optima. The value of the temperature T is updated using Eq.(23):

$$T = \gamma \times T \quad (23)$$

where $\gamma \in [0, 1]$ indicates a random value. The steps in Simulated Annealing are given in Algorithm 3.

Step 1: Set initial temperature T_i, cooling rate CR, minimum temperature T_m

Step 2: Generate an initial candidate solution s

Step 3: Calculate the energy of the initial solution, E

Step 4: Calculate the energy difference ΔE between the new and current solutions and accept a low-energy solution.

Step 5: If the candidate solution has high energy, accept with a probability of energy variation.

Step 6: Repeat steps 2 to 5 until the energy of the current solution is lower than the threshold value or the temperature has reached T_m.

Algorithm 3 Simulated Annealing

3.3.7. Fitness Evaluation using Fine-Grained Tournament Selection

In the traditional ABC algorithm, after the employed bee phase, the fitness of all different food sources is evaluated using Eq.(14) and the probability of selecting one food source based on the fitness value is evaluated using Eq.(13). The algorithm uses a roulette wheel selection strategy to select the best food path based on the fitness value. The drawback of this mechanism is that small values are ignored when the fitness value is negative. Instead of this proportional selection of the fitness value, a fine-grained tournament selection strategy is adopted in the onlooker bee's phase of the RABCO-AODV-RP algorithm. Fine-grained tournament selection is an improved version of the tournament selection method.

The tournament selection method uses an integer control parameterT_i which denotes the size of the tournament. This method does not balance well between exploration and exploitation. To overcome this issue, fine-grained tournament selection uses a real-valued control parameter T_f which is the desired average tournament size.

In the fine-grained tournament selection method, the tournaments contain varying numbers of competitors for the selection process. The average tournament size should be close to T_f. Here, the size of the tournament varies at most by 1. The sizes of tournaments are represented using Eq. (24) and Eq. (25):

$$T_f^- = \mathrm{trunc}(T_f) \quad (24)$$

$$T_f^+ = \mathrm{trunc}(T_f) + 1 \quad (25)$$

The number of tournaments with size T_f^- is calculated using Eq.(26).

$$n^- = trunc(n \times (T_f^+ - T_f)) \quad (26)$$

The number of tournaments with size T_f^+ is calculated using Eq.(27).

$$n^+ = n - n^- \quad (27)$$

The tournaments with size T_f^- *and* T_f^+ are calculated as the best fitted among the T_f^-andT_f^+ individuals.

3.3.8. Exalted Search Using Cauchy Distribution

The employed bees abandon the food source without improvement and become scout bees. The scout bees generate new food sources randomly using Eq.(10) in the traditional ABC algorithm.

The Cauchy algorithm uses the RABCO-AODV-RP distribution to enhance the global region's search operation without falling into local optima. Cauchy is a continuous probability distribution with no expected value and variance. The probability density function of the Cauchy distribution is defined in Eq.(28).

$$f(x; x_0, \gamma) = \frac{1}{\pi}\left[\frac{\gamma}{(x - x_0)^2 + \gamma^2}\right] \quad (28)$$

where x_0 is the location parameter, and γ is the scale parameter. If $x_0 = 0$ and $\gamma = 1$, then the distribution is called the standard Cauchy distribution. Its probability density function is shown in Eq. (29).

$$f(x; 0,1) = \frac{1}{\pi(1 + x^2)} \quad (29)$$

Based on the above details, the pseudo-code of the proposed RABCO-AODV-RP algorithm is shown in Algorithm 4. The framework of RABCO-AODV-RP is given in Figure 1.

Step 1: Set population size S, control parameters $maxcycle$and$limit$.

Step 2: Set initial population Q_i based on a logistic chaotic map in the search space $[P_{min,j}, P_{max,j}]$

Step 3: Generate new search solutions based on the acceptance criterion $P(\Delta E)$ using Algorithm 2

Step 4: Evaluate the solutions based on their fitness and calculate T_f^- andT_f^+ using Fine Grained Tournament Selection Strategy.

Step 5: If the fitness of the new solution did not improve through the control parameter limit, start generating new solutions using the Cauchy distribution.

Step 6: Repeat Steps 2 to 5 until the termination condition is satisfied.

Algorithm 4 RABCO-AODV-RP

3.4. Fusion of RABCO-AODV-RP and AODV

The fusion of RABCO-AODV-RP with the traditional AODV routing protocol enhances energy efficiency and resilience. RABCO-AODV-RP introduces energy-aware route discovery by integrating the Artificial Bee Colony optimization algorithm, reducing energy wastage.

It also ensures adaptability to dynamic network conditions, maintaining reliable communication in the face of changing topologies and node failures. The traditional AODV initiates a route request (RREQ) to find a path to a destination node. Also, it employs a standard route discovery process. The proposed RABCO-AODV-RP integrates the Artificial Bee Colony optimization algorithm into the route discovery phase of AODV.

During this phase, RABCO-AODV-RP intelligently selects energy-efficient routes by considering various factors. The fusion improves the energy efficiency of route selection by choosing paths that minimize energy consumption, enhancing AODV's capabilities.

This integration ensures that the primary enhancement provided by RABCO-AODV-RP is in the route discovery phase of the traditional AODV protocol, optimizing energy consumption and resilience in this critical aspect of routing.

Table 2 shows the difference between AODV routing protocol and RABCO-AODV-RP routing protocol.

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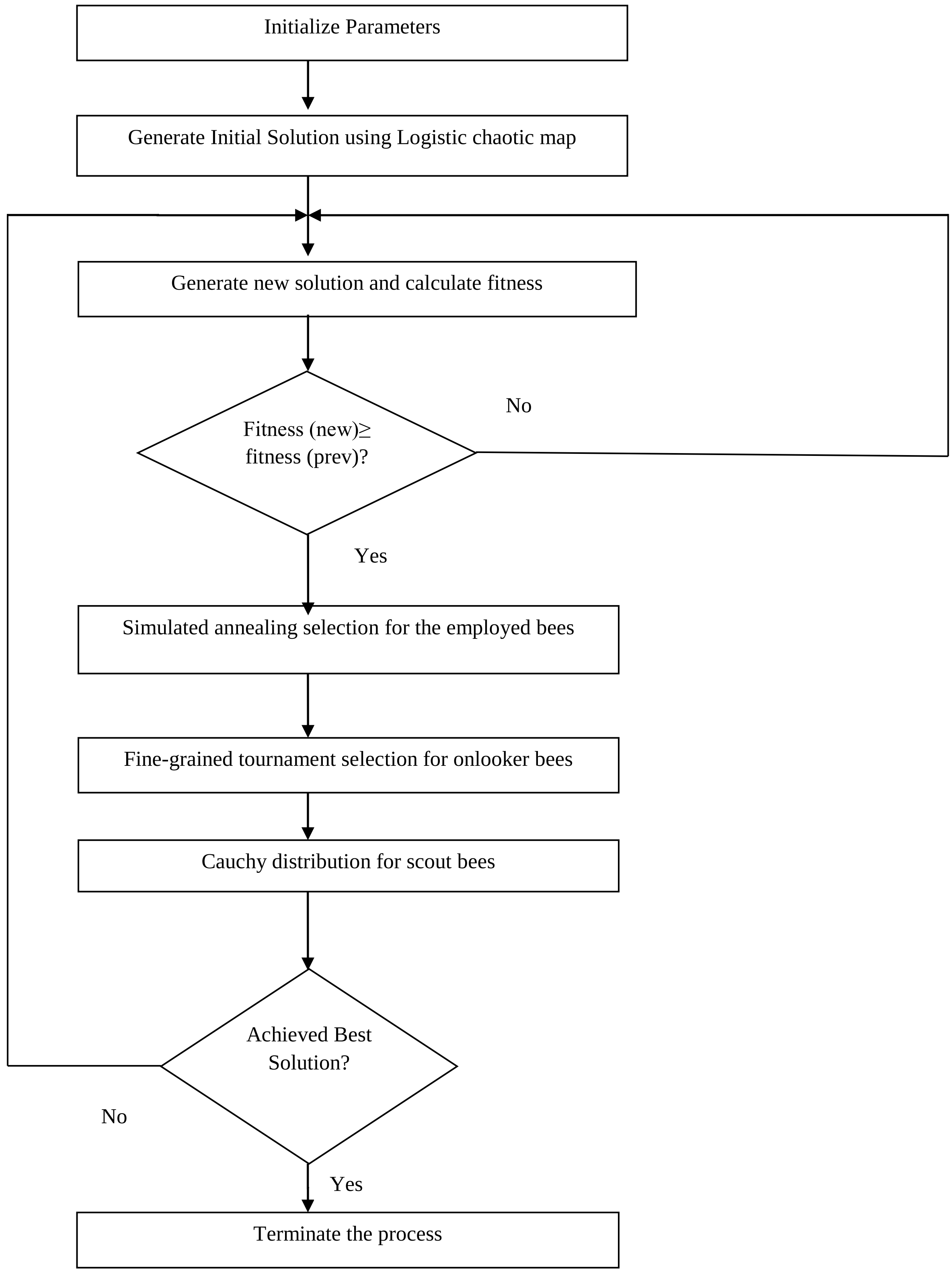

Figure 1 Framework of RABCO-AODV-RP

Table 2 Difference between AODV and RABCO-AODV

Aspect	AODV	RABCO-AODV-RP
Route Discovery	Standard AODV route discovery process.	RABCO-AODV integrates Artificial Bee Colony optimization, reducing energy consumption during route discovery.
Energy Efficiency	Traditional AODV does not inherently optimize energy usage during routing.	RABCO-AODV intelligently selects energy-efficient routes, extending network lifetime.
Resilience to Network Dynamics	AODV may have limited adaptability to dynamic network changes.	RABCO-AODV offers enhanced adaptability, maintaining reliable communication even in changing network conditions.
Network Compatibility	AODV is the base protocol in existing networks.	RABCO-AODV seamlessly integrates with AODV, enhancing energy efficiency and resilience without requiring a full network overhaul.
Algorithm Integration	AODV does not integrate specialized optimization algorithms.	RABCO-AODV incorporates the Artificial Bee Colony algorithm, improving routing efficiency and energy conservation.
Impact on Existing Infrastructure	AODV-based networks require significant modifications for energy efficiency.	RABCO-AODV provides an efficient upgrade without the need for extensive network restructuring.

4. SIMULATION SETTINGS AND PERFORMANCE METRICS

To verify the effectiveness of RABCO-AODV-RP against the state-of-the-art routing protocols and to compare its performance, this research uses Network Simulator Version 3. The mobility model adopted in the simulation is the Random waypoint model. A Binary Phase-Shift Keying modulation scheme is used in the simulation. The simulating setting used in this research is provided in Table 3.

Table 3 Network Simulator Parameters

Aspect	Minimum Value/Setting
Antenna Gain	2 dBi
Carrier Frequency	2.4 GHz (ISM band)
Channel Bandwidth	5 MHz
Coding Scheme	No coding (initially)
Data Traffic Model	Constant bit rate (CBR) for simplicity
Jitter Tolerance	20 ms
Latency Requirements	100 ms
Mobility Model	Random waypoint model
Multi-Path Fading Model	Rayleigh fading model
Network Simulation Framework	NS-3 (Network Simulator 3)
Packet Size	1500 bytes (typical for IP packets)
Path Loss Model	Two-ray ground reflection model

Receiver Sensitivity	-90 dBm
Simulation Time	300 seconds (5 minutes)
Transmit Power	100 mW (for low-power testing)
UAV Count	100 (varying with the difference of 10)
Update Interval	1 second

4.1. Packet Delivery and Drop Ratio Analysis

Figure 2 presents an analysis of the performance of three routing protocols: CHNN-DSR, eAntHoc-Net, and RABCO-AODV-RP. The analysis is based on two important performance metrics: the Packet Delivery Ratio and the Packet Drop Ratio. These metrics are crucial in evaluating the effectiveness of these routing protocols in ad-hoc networks. Packet Delivery Ratio is a metric that measures the percentage of data packets sent from the source that successfully reach their intended destination. A high Packet Delivery Ratio indicates that the routing protocol efficiently delivers data packets. Packet Drop Ratio, on the other hand, measures the percentage of data packets that are dropped during transmission. A low Packet Drop Ratio is desirable as it signifies that a minimal number of packets are lost during the routing process.

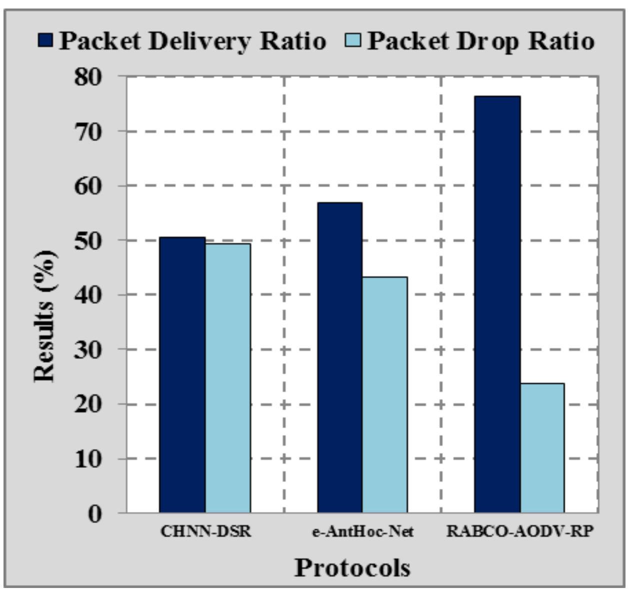

Figure 2 Packet Delivery and Drop Ratio Analysis

CHNN-DSR demonstrates moderate Packet Delivery Ratio (PDR) performance, maintaining an average delivery rate of around 50.63% across network sizes. It’s important to note that CHNN-DSR exhibits a gradual decline in PDR as the network scales up, suggesting that its efficiency in delivering data packets may be sensitive to network congestion and node density. eAntHoc-Net distinguishes itself by consistently achieving a robust Packet Delivery Ratio. With an average delivery rate of approximately 56.75%, it showcases its ability to deliver a substantial portion of data packets across various network sizes. A notable feature of eAntHoc-Net is its resilience in maintaining PDR even in more extensive networks, emphasizing its scalability and reliability. RABCO-AODV-RP stands out as a strong performer in terms of Packet Delivery Ratio. It maintains a high average delivery rate of 76.34% across all network sizes. RABCO-AODV-RP consistently delivers a significant percentage of data packets, even in large-scale networks. This robust delivery performance makes it an excellent choice for applications where dependable communication is a top.

Table 4 Packet Delivery Ratio

Nodes	CHNN-DSR	eAntHoc-Net	RABCO-AODV-RP
10	54.996	62.624	79.835
20	53.825	64.499	78.237
30	55.637	64.061	77.988
40	51.468	60.731	79.589
50	50.769	60.211	78.425
60	51.594	58.957	75.826
70	49.16	55.112	73.193
80	48.408	53.071	73.966
90	47.302	48.216	73.581
100	43.174	40.055	72.773
Average	50.6333	56.7537	76.3413

CHNN-DSR exhibits a moderate Packet Drop Ratio performance, with an average drop rate of approximately 49.37%. It is essential to recognize that CHNN-DSR experiences a slight upward trend in packet drop rates as network size increases, indicating its vulnerability to congestion-induced packet loss in more extensive networks. eAntHoc-Net excels in mitigating packet drops, maintaining an average drop rate of about 43.25%. This underlines eAntHoc-Net’s effectiveness in reducing data loss during transmission, making it an attractive choice for scenarios where minimizing packet drops is crucial. RABCO-AODV-

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RP is exceptional in minimizing packet drops, with an average drop rate of only 23.66%. RABCO-AODV-RP consistently maintains a low packet drop rate across diverse network sizes, underscoring its resilience and robustness in network congestion. Table 4 shows the packet delivery ratio and Table 5 shows the packet drop ratio of the proposed work.

Table 5 Packet Drop Ratio

Nodes	CHNN-DSR	eAntHoc-Net	RABCO-AODV-RP
10	45.004	37.376	20.165
20	46.175	35.501	21.763
30	44.363	35.939	22.012
40	48.532	39.269	20.411
50	49.231	39.789	21.575
60	48.406	41.043	24.174
70	50.84	44.888	26.807
80	51.592	46.929	26.034
90	52.698	51.784	26.419
100	56.826	59.945	27.227
Average	49.3667	43.25	23.66

RABCO-AODV-RP demonstrates clear superiority among the three routing protocols, delivering a high Packet Delivery Ratio and maintaining a significantly low Packet Drop Ratio. This performance underscores its reliability and efficiency, particularly in more extensive networks, where data reliability is paramount.

4.2. Throughput Analysis

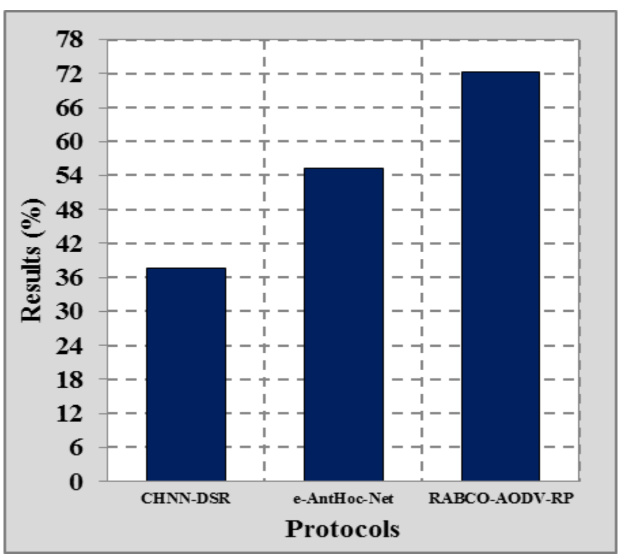

Figure 3 Throughput Analysis

Throughput measures the rate at which data is successfully transmitted through the network, reflecting its capacity to handle data traffic efficiently. Figure 3 depicts the throughput of the proposed RABCO-AODV-RP. Compared to the CHNN-DSR and eAntHoc-Net, RABCO-AODV-RP gives a higher throughput.

Table 6 Throughput

Nodes	CHNN-DSR	eAntHoc-Net	RABCO-AODV-RP
10	31.204	50.305	69.237
20	33.589	50.667	69.478
30	34.958	52.375	69.814
40	35.471	55.482	71.587
50	38.656	55.808	71.825
60	38.882	55.935	72.529
70	39.173	57.117	74.118
80	40.707	57.269	74.493
90	41.125	58.294	74.775
100	42.123	58.901	75.018
Average	37.589	55.215	72.287

CHNN-DSR demonstrates a consistent throughput performance across a range of network sizes. CHNN-DSR achieves an average throughput of approximately 37.59 kbps. Its key strength lies in delivering a reasonably efficient throughput. The protocol shows a gradual increase in throughput as the number of nodes in the network increases, suggesting its capacity to handle higher data traffic in more extensive networks. CHNN-DSR's ability to maintain stable throughput performance makes it a reliable choice, especially in fluctuating node densities. eAntHoc-Net excels in providing robust throughput performance. eAntHoc-Net maintains an average throughput of about 55.22%. This indicates its ability to efficiently manage data traffic within the network. The protocol consistently delivers a substantial throughput rate across different network sizes, emphasizing its reliability and adaptability to diverse network conditions. eAntHoc-Net's capability to maintain substantial throughput, even in more extensive networks, positions it as an ideal choice for applications with critical scalability. RABCO-AODV-RP stands out with exceptional throughput performance. RABCO-AODV-RP boasts an average throughput of approximately 72.29 %, making it a frontrunner in efficiently handling data traffic. This is shown in Table 6. RABCO-AODV-RP consistently delivers the highest throughput across various network sizes, showcasing its unmatched capacity for efficiently transmitting data. The

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protocol's ability to handle high-capacity data traffic makes it an excellent choice for applications requiring rapid data transfer and efficient data communication.

RABCO-AODV-RP emerges as the routing protocol with the most significant contribution in throughput. Its remarkable ability to consistently provide high throughput across various network sizes makes it a standout choice for applications requiring efficient and high-capacity data traffic management. Researchers and network designers should recognize RABCO-AODV-RP's essential contribution to enhancing data transmission in ad-hoc networks, particularly in scenarios where data reliability and speed are paramount.

4.3. End-to-End Delay Analysis

The end-to-end delay is calculated as the time a packet travels from source to destination. Figure 4 shows the end-to-end delay of all three protocols.

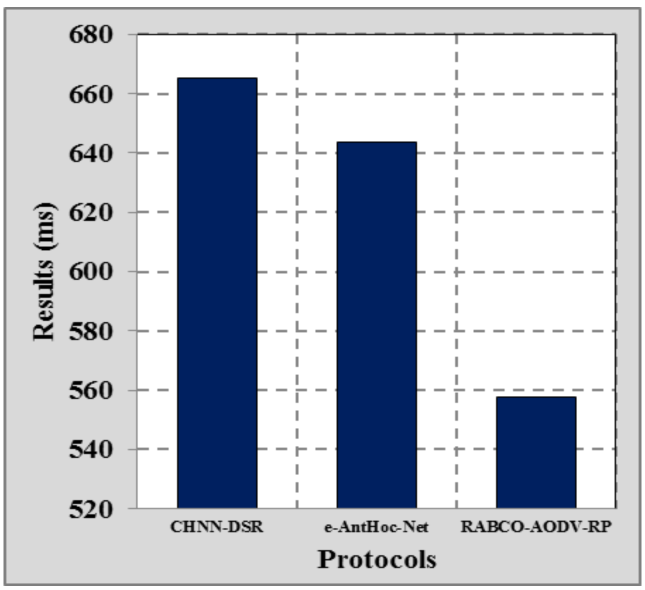

Figure 4 End-to-End Delay Analysis

CHNN-DSR exhibits a consistent and moderate End-to-End Delay, with an average of approximately 665.4 ms. CHNN-DSR consistently provides predictable and moderate delay times, making it suitable for applications where maintaining a steady communication timing is essential. It maintains a stable performance across various network sizes, ensuring that end-to-end communication delays remain acceptable. CHNN-DSR does not achieve the lowest delay times, which may be a disadvantage in applications where minimizing delay is critical. eAntHoc-Net performs well in minimizing End-to-End Delay, averaging approximately 643.8 ms. eAntHoc-Net excels in reducing communication delays, making it a strong choice for applications where low-latency communication is required. The protocol's ability to consistently provide low delay times, even in networks with varying node densities, ensures reliable and efficient communication. While it offers low delays, eAntHoc-Net does not achieve the absolute lowest delay times, which could be a limitation in ultra-latency-sensitive applications.

RABCO-AODV-RP stands out with exceptional performance, providing the lowest End-to-End Delay, with an average of approximately 557.5 ms. This is shown in Table 7. RABCO-AODV-RP consistently delivers the shortest delay times, making it an ideal choice for applications with minimal possible communication delays. The protocol maintains low-delay performance across diverse network sizes, ensuring efficient and rapid data transmission. RABCO-AODV-RP is well-suited for applications that require real-time or low-latency communication. Achieving low delay often involves complex routing strategies, which might increase the protocol's implementation and maintenance complexity. Low latency can be resource-intensive, potentially demanding more energy and bandwidth, which could be a limitation in resource-constrained environments.

RABCO-AODV-RP offers the lowest End-to-End Delay and is well-suited for applications prioritizing minimal communication delays. However, its potential complexity and resource requirements should be considered. CHNN-DSR and eAntHoc-Net, while not achieving the lowest delays, provide predictable and stable performance, making them suitable for various scenarios with less stringent latency requirements.

Table 7 End-to-End Delay

Nodes	CHNN-DSR	eAntHoc-Net	RABCO-AODV-RP
10	632	604	520
20	639	613	524
30	646	621	546
40	655	639	548
50	661	643	551
60	668	647	553
70	675	652	564
80	682	661	583
90	691	675	588
100	705	683	598
Average	665.4	643.8	557.5

4.4. Energy Consumption Analysis

Figure 5 depicts the energy consumption of the existing and proposed protocols. Reducing the energy consumption of mobile nodes in the network is desirable to increase the network lifetime.

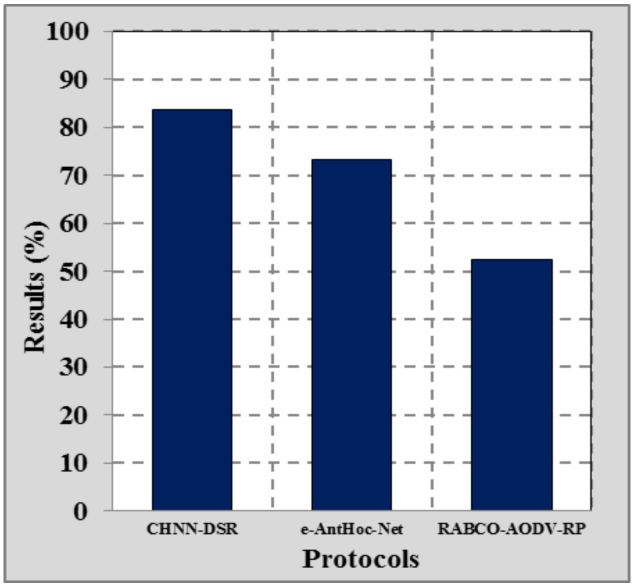

Figure 5 Energy Consumption Analysis

Table 8 Energy Consumption

Nodes	CHNN-DSR	eAntHoc-Net	RABCO-AODV-RP
10	79.475	66.295	47.993
20	80.215	68.921	48.356
30	82.661	69.867	49.816
40	83.346	70.338	50.175
50	83.717	71.268	51.071
60	84.104	74.179	52.164
70	84.987	76.85	53.073
80	85.963	77.499	55.521
90	86.992	78.553	57.126
100	85.117	80.142	59.748
Average	83.658	73.391	52.504

CHNN-DSR demonstrates an average energy consumption of approximately 83.66%. CHNN-DSR’s moderate energy consumption is attributed to its balanced approach, aiming to maintain network performance while keeping energy usage within acceptable limits. It contributes to network versatility and is suitable for scenarios where a trade-off between energy efficiency and performance is necessary. CHNN-DSR’s balanced approach allows it to adapt to various network scenarios, ensuring moderate energy consumption without compromising performance. It may not be the most energy-efficient choice for extremely power-constrained devices or applications with stringent energy conservation requirements.

eAntHoc-Net exhibits an average energy consumption of about 73.39%. eAntHoc-Net achieves lower energy consumption due to its energy-efficient routing strategies and optimizations. Its significant contribution lies in being an energy-efficient protocol, making it an excellent choice for battery-constrained devices and scenarios where energy conservation is a priority. eAntHoc-Net’s energy efficiency contributes to network sustainability and prolongs the operational lifespan of battery-powered devices. While energy-efficient, it may not be the absolute best choice for applications with ultra-strict energy constraints, as it doesn’t reach the energy efficiency level of RABCO-AODV-RP as shown in Table 8.

RABCO-AODV-RP presents the lowest average energy consumption, with approximately 52.50%. RABCO-AODV-RP’s outstanding energy efficiency is achieved through advanced routing optimization and energy-conserving strategies. It excels in energy efficiency, offering the lowest energy consumption, a significant advantage in scenarios where energy preservation is crucial. RABCO-AODV-RP’s energy conservation capabilities extend network operation, reduce energy costs, and enhance overall network sustainability. Achieving such low energy consumption may introduce complexity and potential resource requirements, which could be a drawback in resource-constrained environments or applications where simplicity is favored.

RABCO-AODV-RP is the most energy-efficient protocol among the three, making it an ideal choice for scenarios with strict energy constraints and emphasizing energy conservation. eAntHoc-Net offers good energy efficiency, contributing to the sustainability of networks, particularly in battery-constrained settings. CHNN-DSR provides balanced energy efficiency, making it a versatile choice for scenarios where a compromise between energy consumption and performance is acceptable.

4.5. Hop Count Analysis

Hop count refers to the number of intermediate nodes a packet has to travel from source to destination. An efficient routing protocol tends to find the route with the most minor hop count for effective data delivery.

CHNN-DSR exhibits an average hop count of approximately 436.4 hops. CHNN-DSR’s relatively higher hop count may result from its routing strategy, leading to longer paths to reach the destination. It contributes to network connectivity but at the cost of increased hop count, affecting latency and network efficiency. CHNN-DSR’s approach ensures network robustness and adaptability to dynamic changes but may result in slightly higher hop counts. The increased hop count

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may impact network latency and potentially increase energy consumption.

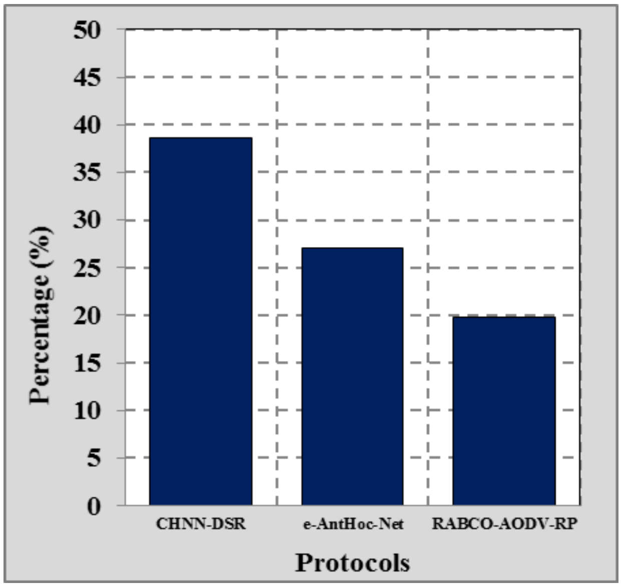

Figure 6 Hop Count

Table 9 Hop Count

Nodes	CHNN-DSR	eAntHoc-Net	RABCO-AODV-RP
10	412	275	184
20	413	286	192
30	422	289	193
40	423	298	200
50	434	303	218
60	435	315	221
70	447	316	244
80	452	319	262
90	458	326	264
100	468	337	265
Average	436.400	306.400	224.300

eAntHoc-Net demonstrates an average hop count of about 306.4 hops. eAntHoc-Net achieves a lower hop count due to its efficient routing strategies and optimized path selection. Its essential contribution is minimizing hop count, enhancing network efficiency, reducing latency, and conserving energy. eAntHoc-Net's low hop count is advantageous in scenarios where rapid data transmission and network efficiency are critical. While achieving a low hop count, it may not prioritize robustness as much as CHNN-DSR, potentially leading to reduced adaptability to dynamic network changes.

RABCO-AODV-RP achieves the lowest average hop count, with approximately 224.3 hops. This is depicted in Figure 6. RABCO-AODV-RP achieves ameager hop count due to its optimization strategies and efficient route discovery. It excels in reducing hop count, contributing to reduced latency, efficient data transmission, and minimizing energy consumption. RABCO-AODV-RP's deficient hop count benefits applications with crucial low-latency and energy-efficient communication. Achieving such a low hop count may involve complex routing algorithms, potentially increasing protocol implementation complexity and resource requirements.

RABCO-AODV-RP achieves the lowest hop count, offering significant advantages in reduced latency and energy efficiency. This is shown in Table 9. eAntHoc-Net provides efficient routing with a low hop count, prioritizing network efficiency. CHNN-DSR ensures network robustness and adaptability but may result in a higher hop count, impacting latency and potentially increasing energy consumption. The choice of protocol should align with the specific network requirements and priorities.

5. CONCLUSION

The Resilient Artificial Bee Colony Optimized AODV Routing Protocol (RABCO-AODV-RP) presents a valuable solution to energy consumption and network resilience challenges in FANETs. By effectively integrating the Artificial Bee Colony optimization algorithm into the traditional AODV routing protocol, RABCO-AODV-RP significantly enhances the energy efficiency of route discovery and adapts to dynamic network conditions. This fusion introduces an intelligent approach to route selection that minimizes energy wastage, extending network operational lifetimes and reducing environmental impact. RABCO-AODV-RP's adaptability to network dynamics ensures it can efficiently maintain communication, even in rapidly changing topologies or node failures. The results of extensive evaluations conducted using the NS3 network simulator underscore the protocol's superior performance in energy efficiency, packet delivery ratios, and network resilience compared to conventional routing protocols. The practical advantage of seamlessly integrating these enhancements into existing AODV-based FANETs positions RABCO-AODV-RP as a promising solution for achieving sustainable and reliable communication in dynamic and resource-constrained FANET environments.

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