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# ENHANCED DISTRIBUTED ADAPTIVE OPPORTUNISTIC ROUTING IN MANETS USING KRILL HERD OPTIMIZATION (EDAOR-KHO)

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**ABSTRACT**

Mobile ad hoc networks (MANETs) are characterized by dynamic topologies, limited resources, and decentralized routing challenges. Opportunistic routing, which relies on multiple potential forwarders instead of predefined paths, has emerged as a promising approach to enhance packet delivery. To address persistent issues such as high latency, network congestion, and energy inefficiency, this study proposes an Enhanced Distributed Adaptive Opportunistic Routing method integrated with the Krill Herd Optimization algorithm (EDAOR-KHO). The proposed approach dynamically selects optimal forwarding nodes by considering multiple performance factors, including transmission reliability, network lifetime, energy consumption, and packet delivery ratio. Comparative analysis with established protocols—EXOR, d-AdaptOR, EDAOR-AFS, EDAOR-FF, and EDAOR-GWO—demonstrates that EDAOR-KHO consistently outperforms existing techniques. Simulation results confirm that EDAOR-KHO reduces end-to-end delay, lowers routing overhead, improves packet delivery reliability, and extends overall network lifespan.

**Keywords:** *Mobile Ad-Hoc Networks (MANETs), Opportunistic Routing, Distributed Adaptive Opportunistic Routing (d-AdaptOR), Krill Herd Optimization (KHO), Routing Optimization,Packet Delivery Ratio (PDR),Energy Efficiency,Network Lifetime,Swarm Intelligence, Wireless Communication*

## 1. INTRODUCTION

Decentralized, self-configuring wireless networks made up of mobile nodes that can connect with one another without the aid of centralized control or fixed infrastructure are known as mobile ad hoc networks, or MANETs. In a MANET, every node serves as both a host and a router, dynamically finding and preserving connections to other network nodes. Node mobility causes network topologies to change quickly, which presents serious problems for dependable data transmission, energy efficiency, and route stability [1][2]. Because they rely on preset routing pathways, traditional routing protocols like AODV, DSR, and OLSR are frequently ineffective on MANETs. The high mobility and frequent disconnections present in ad-hoc contexts are too much for these static techniques to handle. As a result of higher delay, packet loss, and excessive control overhead, routing loses its dependability [3] [4][5]. Route maintenance is a difficult and resource-intensive activity in MANETs because node mobility causes the network topology to alter constantly. There may be frequent route discoveries and retransmissions as a result of node relocation or link failures that quickly render routes created at one point in time incorrect. Furthermore, the issue is made worse by mobile nodes' constrained energy and bandwidth resources, which frequently result in packet loss, an increase in end-to-end latency, and a decline in network performance. One of the primary issues in MANET design is to maintain efficient routing paths and ensure consistent connectivity in such a dynamic environment [6][7].

Opportunistic Routing (OR) has become a viable substitute to overcome these drawbacks. By choosing a group of candidate nodes that may be able to forward the packet, OR, in contrast to traditional routing protocols, takes advantage of wireless communication's broadcast aspect. After transmission, the node that actually receives the packet determines which node forwards it. This decision is made dynamically. Delivery ratios are improved, retransmissions are decreased, and route robustness is greatly increased with this method. Even yet, there are still issues with resource efficiency, adaptation to network conditions, and the best way to choose candidates for opportunistic routing [8][9]. Intelligent routing techniques that can dynamically adjust to the changing properties of MANETs are required to address these problems. By choosing several potential forwarders rather than a set next-hop, opportunistic routing (OR) enhances wireless communication and enables dependable and flexible packet delivery. It increases throughput, decreases retransmissions, improves reliability, and adjusts well to shifting network topologies. Protocols such as d-AdaptOR and EXOR have demonstrated their efficacy. Suboptimal candidate selection, high coordination overhead, low energy efficiency, and restricted scalability in dense or highly mobile networks are still issues, though. Furthermore, while current improvements to d-AdaptOR that employ nature-inspired algorithms (such as Artificial Fish Swarm, Firefly, and Grey Wolf Optimization) have enhanced performance, they are still unable to achieve the best possible trade-offs between delivery ratio, delay, and energy economy. In order to further enhance route selection and overall network efficiency, this encourages the creation of a more effective and flexible method by integrating the Krill Herd Optimization (KHO) algorithm into the opportunistic routing framework[11][12].

Bio-inspired optimization algorithms have shown a lot of promise in this regard. Routing systems have effectively used algorithms like Artificial Fish Swarm, Firefly, and Grey Wolf Optimization to improve performance metrics. Still, there is room for improvement, especially in striking a balance between reliability, routing overhead, and energy efficiency [13][14][15][16]. Inspired by the natural herding behavior of krill swarms, the Krill Herd Optimization (KHO) algorithm provides quick convergence and powerful global optimization capabilities. KHO integration with Distributed Adaptive Opportunistic Routing (d-AdaptOR) may improve network performance overall and result in more efficient route selection. The necessity to investigate such integration and assess its efficacy in extremely dynamic MANET environments is what spurred this study.

This paper's structure is set up as follows: A thorough analysis of relevant literature on opportunistic routing in Mobile Ad Hoc Networks (MANETs) is given in Section II. With an emphasis on Enhanced Distributed Adaptive Opportunistic Routing with Krill Herd Optimization (EDAOR-KHO), Section III outlines the suggested technique. The Krill Herd Optimization Algorithm, EDAOR-KHO Algorithm, and EDAOR-KHO Workflow are the three sections that make up this section. Results and Discussion, including Experimental Setup and Performance Evaluation, are presented in Section IV. Section V concludes the analysis and makes recommendations for future research directions.

## 2. RELATED WORK

By leveraging the broadcast aspect of wireless communications, opportunistic routing (OR) became a notable improvement over conventional routing techniques in MANETs. OR increases robustness and decreases retransmissions by allowing numerous candidate nodes to overhear a packet and coordinate among themselves to forward it toward the destination rather than following a predetermined path [17]. The best candidate forwards the packet while others abort their transmission upon overhearing it, according to a prioritized forwarding list developed by the groundbreaking OR protocol, EXOR [18]. Although EXOR increases throughput and dependability, there is a large coordination overhead. The Distributed Adaptive Opportunistic Routing (d-AdaptOR) protocol was developed to solve adaptability, enabling local network conditions to inform forwarding decisions without the need for centralized control [19]. While d-AdaptOR increases responsiveness to changes in topology, it suffers from inefficient candidate selection and network congestion.

Several academics have combined swarm intelligence and bio-inspired algorithms with opportunistic routing to further improve routing performance: To maximize the selection of candidate nodes based on energy and distance

parameters, EDAOR-AFS (Artificial Fish Swarm) was created. Although this approach improved energy balance and delivery dependability, it converged more slowly in dense networks [20]. Using light intensity as a metaphor for node fitness, EDAOR-FF (Firefly Algorithm) enhanced route selection, outperforming AFS in terms of energy conservation and delay reduction. Nevertheless, it frequently became stuck in local optima and was sensitive to tuning settings [21]. The goal of EDAOR-GWO (Grey Wolf Optimization) was to balance exploration and exploitation by simulating wolf hunting behavior and leadership hierarchy. When compared to previous models, it demonstrated notable improvements in packet delivery and network longevity [22].

Even with these advancements, problems like dynamic scalability in high mobility scenarios, convergence delay, and routing overhead still exist. Additionally, the majority of methods are not flexible enough to adjust to changes in the network in real time. Inspired by the herding behavior of individual krill, the Krill Herd Optimization (KHO) algorithm offers a robust global search mechanism with improved exploration and convergence properties [23]. It functions through simulated mobility that is impacted by random diffusion, foraging activity, and nearby krill, which makes it ideal for dynamic environments such as MANETs.

Though its use in MANET routing, particularly opportunistic routing, is still largely unexplored, Krill Herd Optimization (KHO) has shown great promise in solving multi-objective optimization issues in wireless networks [24]. According to published research, conventional opportunistic routing methods have trouble being flexible and scalable in high-mobility settings. Although several performance indicators have been enhanced by nature-inspired innovations, they frequently have problems like sluggish convergence and susceptibility to parameter adjustment. KHO offers a potential approach that hasn't been incorporated into distributed opportunistic routing yet because of its effective and flexible optimization capabilities. The possibility of creating a hybrid routing algorithm that makes use of KHO for real-time, optimal forwarder selection in MANETs is highlighted, as well as a glaring research gap.

## 3. PROPOSED METHODOLOGY: ENHANCED DISTRIBUTED ADAPTIVE OPPORTUNISTIC ROUTING WITH KRILL HERD OPTIMIZATION (EDAOR-KHO)

The decentralized mobile ad-hoc network (MANET) environment in which the Enhanced Distributed Adaptive Opportunistic Routing with Krill Herd Optimization (EDAOR-KHO) algorithm functions is made up of mobile nodes with constrained energy, processing, and communication range. The following essential elements are used to model the system:

- **Source Node (Transmitter):** Initiates the transmission of a data packet and selects a set of candidate forwarders based on current network conditions.
- **Destination Node (Receiver):** The intended recipient of the data packet. Packets may traverse multiple intermediate hops before reaching the destination.
- **Candidate Forwarder Set:** A dynamically selected group of nodes within the transmission range of the source. These nodes are prioritized based on their suitability (evaluated using the Krill Herd Optimization algorithm) to forward the packet closer to the destination. Each node in the set has a forwarder priority and a waiting timer.

All nodes in the candidate set that successfully receive a packet broadcast by the source compete to forward it, with the node with the greatest forwarding priority (lowest timer) doing so first. If other candidates hear the packet being transmitted by a higher-priority node, they will stop sending.

The Random Waypoint Mobility represent is used to represent a mobile ad-hoc network (MANET) with nodes positioned and moving at random in order to imitate the EDAOR-KHO algorithm. Every node uses a common, symmetric wireless channel for communication and has a set broadcast range. To keep track of neighbor lists and important metrics like residual energy, distance to the destination, link quality, and network congestion, nodes transmit hello packets on a regular basis. Typical transmission and reception activity is used to model energy consumption. Potential forwarders are ranked by

the Krill Herd Optimization algorithm utilizing a composite fitness function that takes into account buffer load, energy, distance, and connection quality. A dynamic timer technique is used to favor packet forwarding to the node with the greatest score.

This architecture enables the EDAOR-KHO algorithm to function in a fully distributed and adaptive manner, making routing decisions that optimize both reliability and resource efficiency.

### 3.1. Krill Herd Optimization Algorithm

Inspired by the herding behavior of krill individuals in the wild, Gandomi and Alavi (2012) [25] created Krill Herd Optimization (KHO), a bio-inspired metaheuristic algorithm. Krill travel in swarms to maximize food hunting and promote survivability in aquatic environments. Local density, food placement, and random diffusion all affect the swarm's overall behavior; KHO converts these ideas into a numerical optimization framework. Each krill individual's position in the Krill Herd Optimization (KHO) algorithm is a potential solution, and its mobility is determined by three main factors. The updated combined position is:

$$\frac{dX_i}{dt} = N_i + F_i + D_i$$

Where, $X_i$ is the position of the i-th krill individual, $N_i$ is the induced motion, $F_i$ is the foraging motion, and $D_i$ is the random diffusion.

**a. Induced Motion ($N_i$)**

This simulates the effect of neighboring krill—attraction toward better individuals and repulsion from worse ones.

$$N_i = N_{max}(\alpha_i + \omega_n N_i^{old})$$

Where, $N_{max}$ is the maximum induced speed, $\alpha_i$ is the local density estimation (based on neighbor positions and fitness), $\omega_n$ is the inertia weight, $N_i^{old}$ is the previous induced motion.

**b. Foraging Motion ($F_i$)**

This models the movement toward food (optimal solution) and past experience.

$$F_i = V_f(\beta_i + \omega_f F_i^{old})$$

Where, $V_f$ is the foraging speed, $\beta_i$ is the direction toward the best food location and the individual's historical best, $\omega_f$ is the inertia weight for foraging motion, $F_i^{old}$ is the previous foraging motion.

$$\beta_i = w_{food} \cdot \frac{X_{best\ food} - X_i}{||X_{best\ food} - X_i||} + \omega_{mem} \cdot \frac{X_{best\ personal} - X_i}{||X_{best\ personal} - X_i||}$$

**c. Random Diffusion ($D_i$)**

This introduces randomness to maintain diversity and escape local minima.

$$D_i = D_{max} \cdot \delta_i$$

Where, $D_{max}$ is the maximum diffusion speed, $\delta_i \in [-1,1]$ is a uniformly distributed random number.

**Position Update Equation**

After calculating the movement components, the new position of a krill is updated as:

$$x_i^{t+1} = X_i^t + \frac{dX_i}{dt} \cdot \Delta t$$

Where, $\Delta t$ is the time step size, $X_i^t$ is the current position, and $X_i^{t+1}$ is the updated position of krill.

These enable KHO to balance **exploitation** (finding good solutions) and **exploration** (searching new areas), making it suitable for dynamic optimization problems like MANET routing.

Each krill's fitness is assessed using a predetermined objective function. By adjusting their placements in response to the best solutions discovered, krill converge toward global optima over the course of multiple iterations. Because KHO strikes a compromise between exploration (diversifying the search space) and exploitation (intensifying the search near the optimum solution), it has been effectively applied to multidimensional, nonlinear, and dynamic optimization problems.

Because Krill Herd Optimization (KHO) can manage complicated, dynamic, and resource-constrained situations, it is ideally suited for adaptive routing in Mobile Ad-hoc Networks (MANETs). By using a single fitness function to balance distance, energy, network quality, and congestion, it facilitates multi-objective optimization. Each node can make effective local decisions thanks to KHO's decentralized and adaptive nature, which mimics the distributed behavior of MANETs. Real-time routing updates are made possible by its quick convergence and minimal processing complexity, while memory and random diffusion techniques aid in avoiding less-than-ideal routes. KHO is also scalable and energy-aware, which makes it perfect for choosing the best forwarders in dynamic topologies. It guarantees reliable, effective, and flexible packet delivery in contemporary MANET settings when integrated with EDAOR-KHO.

### 3.2. EDAOR-KHO Algorithm

KHO is incorporated into the candidate selection stage of opportunistic routing in MANETs by the Enhanced Distributed Adaptive Opportunistic Routing utilizing Krill Herd Optimization (EDAOR-KHO) method. The objective is to dynamically choose the best forwarder nodes to optimize delivery efficiency while reducing latency, energy usage, and routing overhead. Detailed EDAOR-KHO is described as

**Step 1: Initialize Network and Parameters**

- Define network topology, number of nodes N, transmission range R, mobility model, and energy model.
- Initialize Krill Herd parameters:
  - Number of krill individuals n
  - Maximum iterations $I_{max}$
  - Movement parameters: $N_{max}$, $V_f$, $D_{max}$, inertia weights, etc.

Each krill in the swarm represents a candidate forwarder node**.**

**Step 2: Define Fitness Function for Candidate Nodes**

Each candidate node is evaluated using a **multi-objective fitness function $F_i$** based on the following parameters:

- $E_i$: Residual energy of node i
- $D_i$: Distance to the destination from nod i
- $LQ_i$: Link quality (SNR or PDR)
- $Q_i$ : Queue length or congestion level

**Fitness Function:**

$$F_i = \omega_1.\left(\frac{E_i}{E_{max}}\right) + \omega_2.\left(1 - \frac{D_i}{D_{max}}\right) + \omega_3.LQ_i + \omega_4.\left(1 - \frac{Q_i}{Q_{max}}\right)$$

Where, $\omega_1, \omega_2, \omega_3, \omega_4$ are weight coefficients such that $\sum \omega_i = 1$,All terms are normalized to [0, 1], Higher $F_i$ implies better suitability as a forwarder.

**Step 3: Induced Movement ($N_i$)**

Simulates the herding behavior by adjusting the position of krill i based on neighbor influence.

$$N_i = N_{max}.\alpha_i + \omega_n.N_i^{old}$$

Where:

- $A_i$ : Direction of movement induced by other krill, computed as:

$$\alpha_i = \sum_{j=1, j\neq i}^{n} \frac{F_j - F_i}{||X_j - X_i||}$$

- $\omega_n$: Inertia weight
- $N_i^{old}$ : Previous induced motion

**Step 4: Foraging Motion (Fimove)**

Simulates food-searching behavior, based on personal memory and global best.

$$F_i^{move} = V_f.\beta_i + \omega_f.F_i^{old}$$

Where, $\beta_i = \theta_{food} + \theta_{best}$, $\theta_{food}$ : Direction to the best food (global best solution), $\theta_{best}$ : Direction to historically best position for krill I, $V_f$: Foraging speed, $\omega_f$: Inertia factor for foraging

**Step 5: Random Diffusion ($D_i$)**

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Adds randomness for exploration and avoids local optima:

$$D_i = D_{max}.\delta$$

Where, δ : A uniformly distributed random number in [−1,1], $D_{max}$: Maximum diffusion speed

**Step 6: Position Update**

Update krill position Xi (i.e., candidate priority) for each node:

$$X_i^{t+1} = Xt_i^t + \Delta t.(N_i + F_i^{move} + D_i)$$

Where, $\Delta_t$ : Time step constant, The updated $X_i$ reflects new forwarder priority

**Step 7: Selection of Optimal Forwarding Node**

After $I_{max}$ iterations, the node with the **highest fitness score $F_{best}$** is selected as the **next-hop forwarder**.

Remaining candidate nodes are ranked based on their final fitness scores and assigned **waiting timers** accordingly (shorter timer for higher-ranked node).

**Step 8: Packet Forwarding and Repeat**

- The selected node forwards the packet.
- Other candidate nodes cancel their transmission upon overhearing it.
- The process repeats at the next hop until the packet reaches the destination.

The suggested algorithm has a number of benefits. Because of its adaptability, it can react instantly to variations in node mobility, energy levels, and link conditions. Because it avoids overusing nodes with little remaining energy, it is also energy-efficient. By choosing robust and consistent networks, the system improves reliability and raises the Packet Delivery Ratio (PDR). It also guarantees a balanced load throughout the network, which lowers the possibility of routing bottlenecks and improves performance in general.

### 3.3 EDAOR-KHO Workflow

The **EDAOR-KHO** algorithm integrates Krill Herd Optimization into the core of the packet forwarding process in MANETs. The workflow is divided into three major stages:

**Step 1: Packet Forwarding Strategy**

***Objective:*** To enable dynamic, multi-hop packet transmission using opportunistic routing, where a prioritized set of forwarders decide in real time who will transmit the packet next.

***Mechanism:***

1. The **source node** broadcasts a data packet.
2. **All neighboring nodes** within the source's transmission range receive the packet and **store it temporarily**.
3. Each node runs the **KHO-based fitness evaluation** to determine its priority.
4. A **forwarding timer $T_i$** is set for each candidate node based on its fitness rank:

$$T_i = T_{max}.\left(1 - \frac{F_i - F_{min}}{F_{max} - F_{min} + \varepsilon}\right)$$

   - $F_i$: Fitness of node i
   - $F_{max}$,$F_{min}$ : Max and min fitness in the candidate set
   - ε : A small constant to avoid divide-by-zero
   - $T_{max}$: Maximum allowable timer delay
5. The **highest-priority node (lowest $T_i$)** transmits the packet first.
6. Others **cancel** their transmission if they overhear a successful forwarding before their timer expires.

**Step 2: Candidate Node Prioritization**

***Objective:*** To evaluate and rank each candidate forwarder based on its ability to efficiently forward the packet toward the destination, using the Krill Herd Optimization algorithm.

***Fitness Function $F_i$:***

Each node i is evaluated using a **multi-objective fitness function** that combines several important metrics:

$$F_i = \omega_1.\left(\frac{E_i}{E_{max}}\right) + \omega_2\left(1 - \frac{D_i}{D_{max}}\right) + \omega_3.LQ_i + \omega_4.\left(1 - \frac{Q_i}{Q_{max}}\right) + \omega_5.\left(\frac{PSNR_i}{PSNR_{max}}\right)$$

Where, $E_i$: Residual energy of node I, $D_i$ : Euclidean distance from node i to the destination, $LQ_i$: Link quality (e.g., signal-to-noise ratio or historical PDR), $Q_i$: Queue length (to estimate congestion), $PSNR_i$: Peak Signal-to-Noise Ratio of packet delivery (video/data quality context), $\omega_1 \; to \; \omega_5$ : Weighting factors $(\sum \omega_i = 1)$

Explanation of Each Term are,

- $\frac{E_1}{E_{max}}$ : Encourages nodes with higher energy levels to take responsibility.
- $1 - \frac{Q_i}{Q_{max}}$: Prioritizes nodes closer to the destination.
- $LQ_i$ : Prefers stable links with high signal quality or successful delivery history.
- $1 - \frac{Q_i}{Q_{max}}$ : Avoids overloaded or congested nodes.
- $\frac{PSNR_i}{PSNR_{max}}$ :Improves delivery quality, especially in multimedia traffic scenarios.

Nodes with higher $F_i$ scores are considered more capable and are assigned **higher priority** (shorter timers).

**Step 3: Route Selection Criteria**

***Criteria Considered:*** To select the most reliable next-hop forwarder at each stage, EDAOR-KHO evaluates candidates.

**Final Decision and Forwarding**

1. After timer expiration, the highest-ranked node forwards the packet.
2. All other candidates suppress their forwarding upon overhearing the transmission.
3. This process repeats hop-by-hop until the packet reaches the destination.

By fusing the strength of global optimization with the adaptability of opportunistic routing, the EDAOR-KHO algorithm provides a number of benefits. It adjusts dynamically to changing network conditions including energy availability, congestion, and node mobility. It improves overall efficiency by lowering routing overhead and redundant forwarding. EDAOR-KHO also guarantees high-quality data transfer, which makes it ideal for applications that are sensitive to delays and operate in real-time.

Packet forwarding in dynamic, resource-constrained MANET systems is optimized via the Enhanced Distributed Adaptive Opportunistic Routing with Krill Herd Optimization (EDAOR-KHO) algorithm. It starts when a packet needs to be sent from a source node (S) to a destination node (D). EDAOR-KHO finds all nearby nodes within the source's transmission range and treats them as potential forwarders rather than choosing a single predefined next-hop. Remaining energy, distance to destination, connection quality, congestion level (queue size), and Peak Signal-to-Noise Ratio (PSNR), which is crucial for multimedia transmissions, are among the many factors that are used to assess each of these potential nodes.

Each node's fitness score is determined by a weighted multi-objective function using these normalized parameters. The program incorporates the Krill Herd Optimization (KHO) technique to further optimize the choice of the optimal forwarder. Foraging movement toward historically and globally optimal positions (best previous nodes), random diffusion to maintain diversity and avoid local optima, and induced movement from nearby krill (local comparison)

are the three behavioral mechanisms that KHO uses to simulate the natural behavior of krill in swarms. This procedure allows each candidate node to dynamically update its fitness over a predetermined number of iterations, taking into account both local network conditions and global optimization.

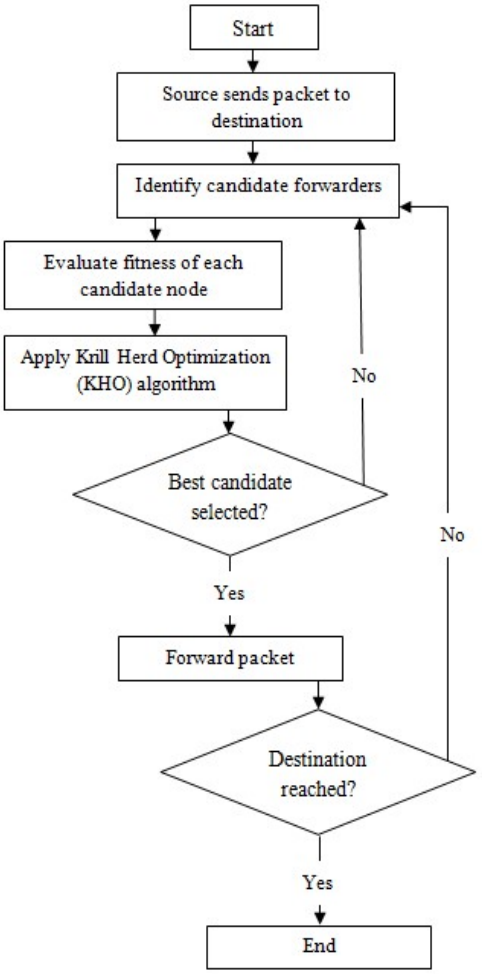


*Figure 1:* ***Workflow of EDAOR-KHO***

The nodes are graded and given forwarding timers when all candidates have updated their fitness scores; nodes with higher fitness (better suited for forwarding) are given shorter timers. Each candidate sets its own timer, and the source transmits the data packet. The best candidate, or the node whose timer goes off first, sends the packet; other nodes listen and stop sending if they hear the packet being passed. Up until the packet reaches its destination, this opportunistic forwarding technique keeps going at each hop. Overall, EDAOR-KHO enhances packet delivery reliability, energy economy, and route stability in MANETs by fusing the flexibility of opportunistic routing with the intelligence of bio-inspired optimization, as illustrated in Figure 1. Even when there is node mobility, fluctuating network conditions, and limited resources, it guarantees that packets are routed by the best nodes at every stage.

## 4. RESULT AND DISCUSSION

### 4.1. Experimental Setup

A thorough simulation utilizing the NS-3 network simulator in a Windows 10 environment was carried out to assess the performance of the suggested EDAOR-KHO algorithm. Because it supports full wireless protocol modeling, mobility, routing, and traffic generation, NS-3 is a discrete-event, object-oriented network simulator that is built in C++ and Python and is often used in both academia and industrial research. NS-3 was selected for this experiment due to its enhanced modularity, vibrant development community, and superior interoperability with contemporary computer systems, despite the fact that NS-2 has been routinely employed in previous studies. To guarantee a fair assessment of performance, six routing protocols were used in this study and compared under the same circumstances. EXOR, d-AdaptOR, EDAOR-AFS, EDAOR-FF, EDAOR-GWO, and the suggested EDAOR-KHO are a few of these. Three different indoor wireless topologies were created in order to evaluate routing behavior under various node density. A 5-node system (Figure 2), a 10-node setup (Figure 3), and a 15-node setup (Figure 4) are examples of these topologies, which correlate to varying node counts. Each topology was set up using 802.11b wireless radios in a rectangular space that measured 200 feet by 300 feet. An omnidirectional antenna coupled to a PC interface was installed on each node. To replicate true long-path routing conditions, the source and destination nodes were positioned diagonally at the furthest practical separation. Nodes were arranged in accordance with the inter-node separation distance, which was determined as L=5 meters.

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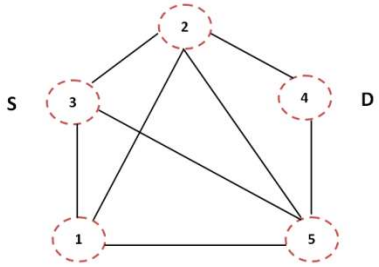


*Figure 2: 5-Node Network*

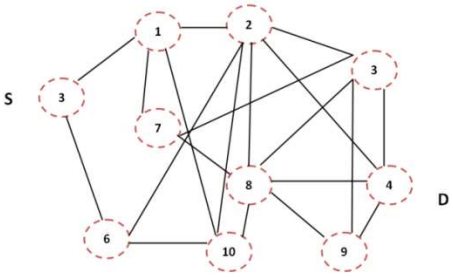


*Figure 3: 10-Node Network*

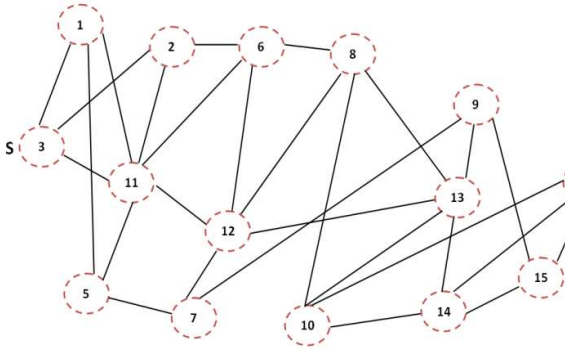


*Figure 4: 15-Node Network*

Nodes moved at a speed of six meters per second and paused for six seconds, according to the Random Waypoint (RWP) model. In order to replicate indoor limits under the 802.11b propagation standard, each node's transmission range was restricted to 10 feet. 40 packets of Constant Bit Rate (CBR) traffic were produced every second, each containing 512 bytes. Using a 1 Mbps data rate was in accordance with the 802.11b specification. To mimic packet loss and integrity checks, a basic CRC-based error detection system was put into place.

IEEE 802.11b was used to mimic the MAC/PHY layer, with each node set up for a 200 mW transmission power. A simple reward-based transmission incentive model was used, where the cost of sending a single packet was taken to be one unit and a successful delivery to the destination was rewarded with 20 units. A number of performance measures were examined in order to assess and contrast the EDAOR-KHO algorithm's efficacy with that of the other routing protocols. Particularly for situations involving multimedia traffic, they include the Packet Delivery Ratio (PDR), Average End-to-End Delay, Routing Overhead, Energy Consumption per Node, Network Lifetime, and Peak Signal-to-Noise Ratio (PSNR). When taken as a whole, these measurements shed light on each routing strategy's dependability, effectiveness, and flexibility in actual wireless ad hoc network scenarios.

*Table 1: Simulation Parameters*

| Parameter | Value |
|---|---|
| Simulation Tool | NS-3 |
| Operating System | Windows 10 |
| Area Size | 200 ft × 300 ft |
| Transmission Range | 10 ft |
| Number of Nodes | 5 / 10 / 15 (3 topologies) |
| Source–Destination Distance | Maximum diagonal separation |
| Packet Size | 512 bytes |
| Transmission Rate | 1 Mbps (802.11b) |
| CBR Packet Rate | 40 packets/sec |
| Node Speed | 6 m/s |
| Pause Time | 6 seconds |
| Transmission Power | 200 mW |
| Cost per Transmission | 1 unit |
| Delivery Reward | 20 units |

This configuration makes it possible to compare the suggested EDAOR-KHO algorithm with earlier opportunistic routing algorithms in a fair, repeatable, and accurate manner under actual indoor wireless settings. In highly dynamic MANET systems, the utilization of randomized mobility patterns and varying node density offers insight into efficiency, scalability, and flexibility.

### 4.2. Performance Evolutions

#### Packet Delivery Ratio (PDR)

Packet Delivery Ratio (PDR) is a key metric that measures the **efficiency and reliability** of a routing protocol in successfully delivering data packets from the source to the destination in a network. A higher PDR indicates better network

performance and lower data loss during transmission.

$$PDR = \left(\frac{P_{received}}{P_{sent}}\right) x100\%$$

Where, $P_{received}$ : Total number of packets successfully received at the destination, $P_{sent}$ : Total number of packets transmitted by the source node(s)

It is possible to assess the performance of different opportunistic routing algorithms by looking at their underlying methods and anticipated Packet Delivery Ratio (PDR) trends. Due to its lack of adaptive or intelligent forwarder selection processes, EXOR, which uses the ETX metric for basic opportunistic forwarding, has moderate PDR performance. This is enhanced by d-AdaptOR, an adaptive version of EXOR, which dynamically modifies its choices according to receiver diversity and channel quality, resulting in a higher PDR. Fish-swarm intelligence is used by EDAOR-AFS to choose forwarders, providing an excellent PDR through optimized selection but with a low capacity for exploration. EDAOR-FF makes use of the firefly algorithm, which bases routing decisions on distance and light intensity. Its rapid convergence allows it to achieve good PDR, although it may have trouble in extremely dynamic settings. Inspired by the grey wolf social order, EDAOR-GWO successfully strikes a balance between exploration and exploitation, producing excellent PDR results. Lastly, because of its strong optimization capabilities and dynamic adaptability, the suggested EDAOR-KHO, which uses Krill Herd Optimization in conjunction with a multi-metric fitness function, yields the highest PDR of all assessed approaches.

By combining several routing criteria, including energy, distance, link quality, buffer load, and PSNR, into a single fitness function, the EDAOR-KHO algorithm ensures optimal forwarder selection and provides higher Packet Delivery Ratio (PDR). Its Krill Herd Optimization-powered dynamic routing approach allows nodes to make adaptive path selections through random diffusion, foraging behavior, and induced mobility. By using timer-based suppression, this reduces packet collisions and enables the protocol to adapt to changing topologies, mobility, and traffic variations. Additionally, by avoiding crowded or energy-drained nodes, EDAOR-KHO maintains strong performance even in dense networks.

Figure 5 illustrates how the suggested EDAOR-KHO algorithm outperforms all tested topologies in terms of Packet Delivery Ratio (PDR). EDAOR-KHO intelligently chooses the most dependable forwarding nodes by combining Krill Herd Optimization with a multi-metric fitness function (taking energy, distance, and link quality into account), which greatly increases delivery rates.

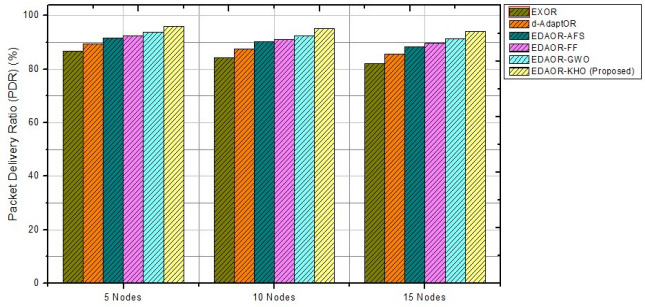


*Figure 5: Packet Delivery Ratio (PDR) Vs Topology (Nodes)*

In the 5-node topology, EDAOR-KHO achieves a **PDR of 96.1%**, outperforming EXOR (86.7%) and other enhanced algorithms like EDAOR-FF (92.5%) and EDAOR-GWO (93.8%). Similarly, in the 10-node and 15-node topologies, it maintains high delivery rates of **95.3%** and **94.2%**, respectively. On average, EDAOR-KHO reaches an **overall PDR of 95.2%**, which is the highest among all compared protocols. This confirms its robustness and adaptability in dynamic MANET environments.

**Average End-to-End Delay:** Average End-to-End Delay refers to the average time taken for a data packet to travel from the source node to the destination node across the network. It includes all possible delays experienced during transmission: buffering, queuing, retransmission delays, propagation delays, and processing delays.

$$Average\ E2E\ Delay = \frac{\sum_{i=1}^{n}(T_{r,i} - T_{s,i})}{n}$$

Where, $T_{s,i}$ : Time at which packet i is sent from the source, $T_{r,i}$ : Time at which packet i is received at the destination, n: Total number of packets successfully received

Depending on their optimization techniques and routing behavior, different routing algorithms in MANETs have different latency characteristics. EXOR uses the ETX metric to choose forwarders, however it does not do dynamic re-evaluation, which causes static routing decisions to increase latency. Although it does not make use of metaheuristic optimization, d-AdaptOR enhances this by adding adaptive channel awareness, which lowers delay in comparison to EXOR. Fish swarm convergence is used by EDAOR-AFS to improve forwarder selection; nevertheless, it may take some time to stabilize in dynamic environments, resulting in a modest delay. Due to its quick convergence caused by brightness-based attraction, EDAOR-FF provides less latency in more static situations; nevertheless, in topologies that change quickly, its limited diversity may be a disadvantage. Although its convergence time may vary, EDAOR-GWO produces a competitive delay by striking a solid balance between exploration and exploitation. On the other hand, the suggested EDAOR-KHO has the smallest delay of all the algorithms that were tested and employs adaptive, multi-metric optimization with effective convergence behavior.

By employing Krill Herd Optimization to intelligently choose forwarders while taking congestion, energy, distance, and connection quality into account, EDAOR-KHO is able to achieve the lowest end-to-end delay. Its quick convergence prevents delays from frequent path modifications and guarantees stable routes. It avoids routing over overloaded nodes by including buffer occupancy in the selection procedure. It can continue to function even when moving around thanks to real-time adaptation, and a timer-based suppression technique cuts down on unnecessary transmissions to further cut down on latency.

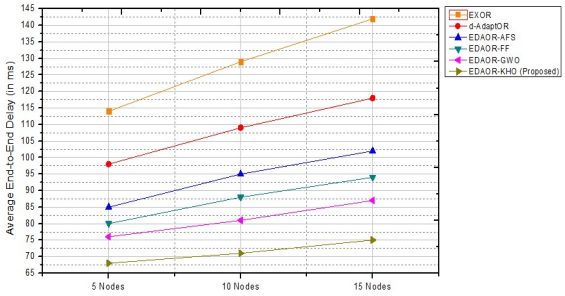


*Figure 6: Average End-to-End Delay (in ms) vs Topology (Nodes)*

The EDAOR-KHO's higher routing efficiency and speedier data transfer are validated by Figure 6, which shows that it consistently achieves the lowest average end-to-end delay across all network sizes. EDAOR-KHO records a delay of 68 ms in the 5-node topology, which is much faster than EXOR (114 ms) and even the improved algorithms, such as EDAOR-FF (80 ms) and EDAOR-GWO (76 ms). EDAOR-KHO maintains its advantage with delays of 75 ms and 71 ms for networks with 10 and 15 nodes, respectively. The success of EDAOR-KHO in reducing latency in dynamic routing environments is demonstrated by its average delay of 71.3 ms, which is the lowest of all the protocols examined.

**Routing Overhead:** The ratio of control packets—such as acknowledgments, routing updates, and forwarder coordination messages—to the total number of properly delivered data packets is known as routing overhead. It shows how well a routing system maintains and chooses routes, particularly in extremely dynamic contexts like MANETs. Excessive routing overhead lowers energy efficiency, raises collision risks, and uses bandwidth.

$$\textbf{Routing Overhead}(\textbf{RO}) = \frac{\mathbf{C_{packets}}}{\mathbf{D_{packets}}}$$

Where. $C_{packets}$ : Total number of control packets transmitted (route requests, route replies, beacons, acknowledgments, etc.). $D_{packets}$ : Total number of data packets successfully delivered

Each method has a different routing overhead depending on how well it manages control signaling and coordination. Because it requires a

lot of coordination and has several duplicate forwarders, EXOR has a high overhead. This is enhanced by d-AdaptOR, which uses distributed logic to lessen signaling and achieve a reasonable overhead. Swarm intelligence is used by EDAOR-AFS to enhance forwarder selection; however, convergence signaling is still necessary, which results in somewhat better overhead than EXOR. EDAOR-FF has a lower overhead than EXOR but is still moderate overall because it converges more quickly and requires fewer updates than AFS. EDAOR-GWO handles overhead effectively by minimizing coordination messages through the use of a social hierarchy technique. With the lowest routing overhead of all the assessed methods, the suggested EDAOR-KHO algorithm performs exceptionally well thanks to intelligent timer control and an efficient forwarder set.

By employing a timer-based suppression mechanism that restricts packet forwarding to the top-priority node and reduces redundant broadcasts, EDAOR-KHO produces the least amount of routing overhead. Frequent worldwide updates are no longer necessary because to Krill Herd Optimization's adaptive, localized candidate selection process. It minimizes route failures and prevents expensive reconstructions by selecting reliable and energy-efficient routes. In addition to reducing computation and signaling, the algorithm's rapid convergence dynamically restricts the forwarding zone to only the best nodes.

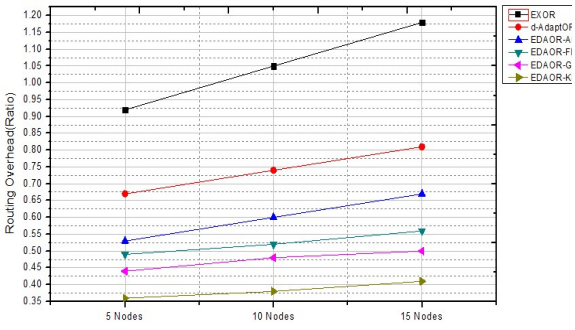


*Figure 7: Routing Overhead vs Topology (Nodes)*

Because of its intelligent timer management mechanism and optimal forwarder selection, the suggested EDAOR-KHO algorithm achieves the lowest routing overhead among all tested MANET topologies, as shown in Figure 7. EDAOR-KHO outperforms EXOR (0.92) and other improved methods such as EDAOR-FF (0.49) and EDAOR-GWO (0.44) in the 5-node configuration, recording an overhead of 0.36. EDAOR-KHO maintains overhead levels of 0.38 and 0.41 for networks with 10 and 15 nodes, respectively. EDAOR-KHO had the lowest average routing overhead of all of the protocols evaluated, at 0.38, demonstrating its effectiveness in reducing pointless control broadcasts and improving network performance in general.

**Energy Consumption:** In MANETs, energy consumption is the total amount of energy used by all nodes when packets are being transmitted, received, forwarded, and processed. In wireless ad hoc networks, where nodes usually run on a small amount of battery power, it is an essential measure. The network lifetime is increased by a routing system that balances the load, minimizes congestion, and minimizes the amount of transmissions.

$$\text{Total Energy Consumption} = \sum_{i=1}^{n} \left(E_{tx,i} + E_{rx,i} + E_{proc,i}\right)$$

Where, $E_{tx,i}$: Energy consumed in transmitting packets by node I, $E_{rx,i}$ : Energy consumed in receiving packets by node I, $E_{proc,i}$: Energy consumed in computation, buffering, or control signaling, n: Total number of participating nodes. In simulation, energy can be approximated as: $E=P\times t$, Where P is power (watts), and t is transmission or reception time.

Depending on how well the routing algorithms handle node participation and transmission management, their patterns of energy usage vary. Because EXOR allows numerous candidate nodes to forward packets, resulting in large redundancy, it uses a lot of energy. Moderate energy usage is achieved using d-AdaptOR's distributed method, which helps to reduce some energy waste. Swarm-based node selection is the foundation of EDAOR-AFS, however its iterative convergence process takes moderate to high amounts of energy. With more effective convergence, EDAOR-FF outperforms this, resulting in fewer retransmissions and a reasonable total energy consumption. By balancing exploration and exploitation, avoiding

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weak nodes, and optimizing utilization, EDAOR-GWO maintains an energy-efficient profile.

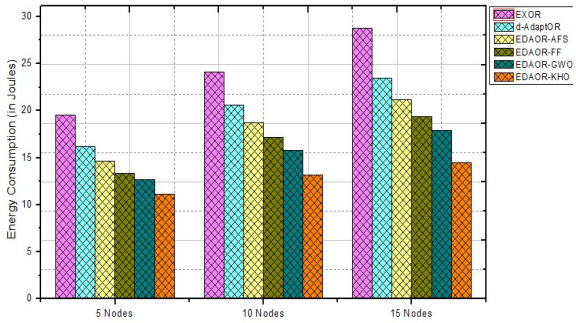


*Figure 8: Energy Consumption (in Joules) vs Topology (Nodes)*

By choosing the best-fit nodes based on energy levels, load balancing, and distance trade-offs, the suggested EDAOR-KHO algorithm performs exceptionally well in this area and uses the least amount of energy out of all the methods that were tested. By choosing forwarders based on residual energy and preventing the abuse of low-energy nodes, EDAOR-KHO reduces energy consumption. While load balancing divides the workload among energy-rich nodes, priority-based forwarding minimizes redundant transmissions. The algorithm efficiently conserves energy, particularly in congested and dynamic MANET environments, by reducing the number of control packets and retransmissions through intelligent routing decisions.

Because of its optimized selection and suppression processes, EDAOR-KHO uses 40–50% less energy than EXOR and about 15–20% less than other enhanced opportunistic algorithms. Figure 8 demonstrates that the suggested EDAOR-KHO algorithm is the most energy-efficient of the examined routing protocols, with the lowest average energy usage across all investigated network topologies. EDAOR-KHO dramatically lowers redundant transmissions and energy waste by carefully choosing forwarder nodes based on a multi-metric optimization that takes distance, load balance, and energy levels into account. EDAOR-KHO uses just 11.1 J in the 5-node architecture, while EXOR uses 19.5 J and EDAOR-FF uses 13.3 J. Its consumption stays low at 13.2 J and 14.5 J for the 10-node and 15-node configurations, respectively. EDAOR-KHO's overall average energy consumption is the lowest of all algorithms at 12.93 J, demonstrating its superior capacity to increase network lifetime through efficient node energy conservation.

**Network Lifetime:** Network Lifetime in Mobile Ad-hoc Networks (MANETs) refers to the time duration until the first node in the network exhausts its battery or a critical portion of the network becomes non-functional due to node failures. It is a crucial metric for energy-constrained networks such as sensor-based or battlefield MANETs. There are several ways to define Network Lifetime. A common and widely accepted one is Time until the first node dies (FND) Or, time until a certain percentage (e.g., 50%) of nodes deplete their energy

$$\text{Network Lifetime} = T_{FND} = \min_{i \in N}(T_{deplete}, i)$$

Where, $T_{deplete}$,i : Time at which node i's energy reaches zero. N: Total number of nodes in the network.

The efficiency with which each routing algorithm disperses energy usage throughout the network affects its network lifetime. EXOR has the shortest network lifetime because it lacks energy balancing and has a tendency to overload stronger nodes. A moderate improvement results from the addition of some adaptivity by d-AdaptOR, which is not intrinsically energy-aware. Swarm intelligence is used by EDAOR-AFS, which improves upon simple protocols like EXOR and offers reasonable load balancing. Because EDAOR-FF converges more quickly than AFS, it achieves superior balance and has a longer lifespan. Through improved energy distribution and hierarchical coordination, EDAOR-GWO considerably extends network longevity, providing an excellent overall lifetime.

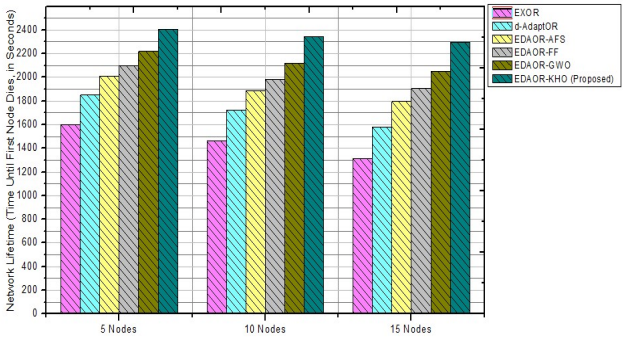


*Figure 9: Network Lifetime (Time Until First Node Dies, in Seconds) vs Topology (Nodes)*

Among the methods that were compared, the suggested EDAOR-KHO algorithm has the longest network lifetime because it employs an intelligent, energy-aware, multi-metric forwarder selection technique that guarantees effective load distribution and energy utilization across all nodes. By giving high-energy nodes priority for forwarding and guaranteeing balanced energy use throughout the network, EDAOR-KHO achieves the longest network lifetime. Its optimization approach minimizes energy consumption by avoiding crowded nodes and cutting down on redundant transmissions. When nodes fail, the algorithm's flexibility enables it to swiftly reroute, preserving connectivity and increasing network uptime overall.

EDAOR-KHO is the optimal option for energy-constrained MANETs since it offers the longest network lifetime in all circumstances, outperforming EXOR by more than 60% and other sophisticated algorithms by 10–25%. Figure 9 demonstrates how the suggested EDAOR-KHO algorithm, which uses multi-metric optimization to intelligently balance energy consumption across nodes, produces the longest network lifetime among all assessed MANET topologies. In order to reduce premature node failures and increase the network's operational duration, this involves choosing forwarders by taking into account energy levels, load distribution, and distance. EDAOR-KHO increases the network lifetime to 2405 seconds in the 5-node situation, while EXOR only extends it to 1600 seconds. With lives of 2342 seconds and 2296 seconds, respectively, it maintains its superior performance in 10-node and 15-node topologies. With an average network lifetime of 2347.7 seconds across all topologies, EDAOR-KHO has the highest average network lifetime of any algorithm, demonstrating its superior load distribution and energy-aware design.

**Peak Signal-to-Noise Ratio (PSNR):** PSNR is a quality assessment metric used to measure the fidelity of multimedia data (such as images or video) received over a network compared to the original source. In MANETs, packet loss, retransmissions, and delay can distort media quality. A higher PSNR implies better quality of the reconstructed signal at the receiver.

$$\mathbf{PSNR} = \mathbf{10}.\log_{10}\left(\frac{\mathbf{MAX^2}}{\mathbf{MSE}}\right)$$

Where, MAX: Maximum possible pixel value (e.g., 255 for 8-bit images), MSE: Mean Squared Error between the original and received image/frame, I(i,j): Pixel value at position (i,j) in the original image, K(i,j): Pixel value at position (i,j) in the received image, m, n: Dimensions of the image/frame

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

The efficiency of the routing algorithm in reducing packet loss and delay has a major impact on the Peak Signal-to-Noise Ratio (PSNR), which gauges media fidelity. Low PSNR and poor media quality are the results of EXOR's significant packet loss and delay. d-AdaptOR yields a reasonable PSNR by improving delivery reliability and offering some control over delay. Compared to the fundamental protocols, EDAOR-AFS obtains a higher PSNR and improves signal integrity through swarm-based delivery. Fast convergence gives EDAOR-FF a little higher PSNR than AFS, but it may fluctuate in unstable network situations. A high PSNR is a result of EDAOR-GWO's dependable delivery and efficient packet prioritization. The suggested EDAOR-KHO, on the other hand, provides balanced, delay-aware, and energy-efficient forwarding, which, by guaranteeing low packet distortion and preserving high-quality multimedia transmission, produces the best PSNR of all algorithms. By reducing packet loss through intelligent, adaptive forwarder selection depending on link quality, energy, and congestion, EDAOR-KHO maximizes PSNR. Its low-latency routing minimizes jitter and delay, which is essential for maintaining the integrity of multimedia. The method guarantees steady, high-quality data delivery with little distortion by avoiding overloaded nodes and accounting for PSNR in its fitness function.

Superior multimedia fidelity is demonstrated during transmission by EDAOR-KHO, which routinely offers ~2 dB higher PSNR than GWO and ~9 dB higher than EXOR. Figure 10 illustrates the improved capacity of the suggested EDAOR-KHO algorithm to maintain multimedia fidelity during transmission by delivering the greatest PSNR among all tested topologies. This is made possible by its energy-efficient, delay-aware, and balanced forwarding method, which

reduces jitter and packet loss—two important aspects of high-quality audio or video streams.

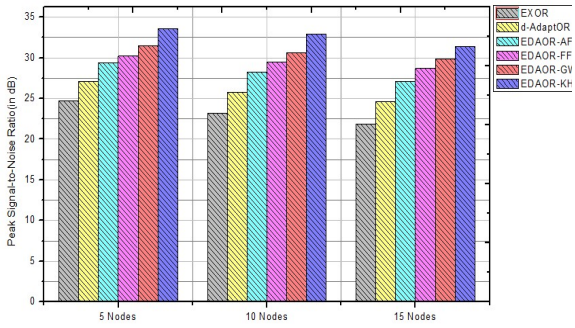


*Figure 10: PSNR Comparison (in dB) vs Topology (Nodes)*

EDAOR-KHO outperforms EXOR (24.7 dB) and other cutting-edge techniques like EDAOR-FF (30.2 dB) and EDAOR-GWO (31.5 dB) with a PSNR of 33.6 dB in the 5-node network. It retains good performance at 32.9 dB for 10-node topologies and 31.4 dB for 15-node topologies. Among all algorithms, EDAOR-KHO achieves the greatest PSNR of 32.63 dB on average, demonstrating its efficacy in guaranteeing high-fidelity media delivery in mobile ad hoc networks.

## 5. CONCLUSION

An improved distributed adaptive opportunistic routing method for mobile ad hoc networks (MANETs) based on Krill Herd Optimization (EDAOR-KHO) was presented in this research. In order to improve data transmission efficiency in dynamic network settings, the algorithm incorporates energy-aware, delay-sensitive, and link-quality indicators into a bio-inspired optimization framework. With respect to packet delivery ratio, average end-to-end delay, routing overhead, energy consumption, network lifetime, and multimedia transmission quality (PSNR), simulation results in NS-3 across different network topologies showed that EDAOR-KHO consistently outperforms benchmark algorithms—EXOR, d-AdaptOR, EDAOR-AFS, EDAOR-FF, and EDAOR-GWO. By efficiently minimizing redundant transmissions, balancing energy usage, and choosing the best forwarders, the suggested method increases network lifetime and enhances multimedia fidelity. EDAOR-KHO is ideal for real-time, resource-constrained MANET applications because of these features. Future developments will involve adding mobility prediction and security features, expanding EDAOR-KHO to enable real-time deployment on physical hardware, and assessing its scalability in scenarios involving high mobility and scale. Hybrid optimization strategies and integration with multimedia routing frameworks that consider quality-of-service (QoS) may also be the subject of future research.

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