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An Intelligent Grey Wolf Optimization Framework for Parameter Adaptation in EAOMDV Routing Protocol

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Abstract: In this paper, a parameter adaption method is suggested for MANET routing efficiency enhancement. It combines the EAOMDV protocol with intelligent Grey Wolf Optimization (GWO). Improving the network's routing patterns through the use of several quality-of-service (QoS) indicators is the main goal. Some of these metrics are the rate of packet delivery (PDR), residual energy, end-to-end delay, and routing overhead. By merging normalized performance measures into a single fitness function, the suggested strategy reframes a weighted single-objective problem as route optimization. In order to automatically optimize routing parameters and choose ideal routes, the suggested system uses GWO, which is modeled after the pack structure and hunting methods used by grey wolves. Better fault tolerance and route stability are achieved by the use of EAOMDV, which guarantees the preservation of multiple loop-free pathways. To avoid optimizing faulty or redundant paths, a method called discrete path validation is used. Many simulations have been run with different node densities and mobility parameters. The proposed GWO-EAOMDV framework outperforms both traditional EAOMDV and alternative optimization-based routing protocols. Reduces end-to-end latency by 15-22% while simultaneously enhancing PDR by 12-18% and improving energy efficiency. The robustness of the proposed model was confirmed by statistical validation employing several simulation runs.

Keywords: Adhoc Networks, Routing Protocols, Packet Delivery Ratio, Throughput, Dynamic, Environment, Grey Wolf Algorithm and EAOMDV.

1. Introduction

The rapid evolution of wireless communication technologies has fundamentally transformed modern connectivity, significantly reducing the reliance on traditional wired networks. Unlike wired systems, which are often characterized by high deployment costs, rigid infrastructure, and complex maintenance requirements, wireless networks offer unparalleled mobility and scalability [1-3]. These advancements allow users to communicate and travel freely without the physical constraints of cables. Furthermore, recent advances in encryption and network protocols have addressed longstanding reliability concerns, making wireless networks more secure and ubiquitous than ever before [4].

Broadly, wireless networks are classified into two distinct architectures: infrastructure-based and infrastructure-less. Infrastructure-based networks rely on a centralized backbone, where devices communicate via fixed hardware units such as access points or base stations [5]. In contrast, infrastructure-less networks, commonly known as Ad Hoc networks, operate without any pre-existing central administration. In this decentralized topology, devices connect dynamically and directly with one another.

A defining characteristic of Ad Hoc networks is the dual role of the participating nodes; each device functions as both a host and a router. Since every node has a limited transmission range, communication between distant nodes requires "multi-hop" data transmission. Here, intermediate nodes cooperate and moves the packets from the source to the destination, bridging the gap when the receiver is outside the sender's direct radio range. This autonomy and self-configuration make Ad Hoc networks a cost-effective and rapidly deployable solution [6, 7]. These networks are generally categorized into three primary types: Wireless Sensor Networks (WSN), Wireless Mesh Networks (WMN), and Mobile Ad Hoc Networks (MANET).

Within the spectrum of wireless systems, MANETs have achieved prominence, particularly in defence logistics and emergency response scenarios which often lead to link instability and network partitioning [8-10]. Unlike fixed infrastructure systems, MANET efficacy relies heavily on the cooperative forwarding of data packets; however, this fluidity presents significant obstacles regarding Quality of Service (QoS) and resource allocation. Addressing this routing optimization is an NP-hard problem, where traditional mathematical methods often struggle to dynamically balance energy, latency, and throughput in real-time. Consequently, researchers have turned to meta-heuristic techniques based on Swarm Intelligence (SI), such as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), which mimic collective natural behaviours to solve complex problems [11]. Among these, the Grey Wolf Optimizer (GWO) has emerged as a powerful SI technique; inspired by the chase mechanism and social hierarchy of grey wolves, GWO offers superior convergence speed and avoids getting trapped in local optima, making it an ideal candidate for optimizing routing parameters in energy-constrained networks [12].

In [13], addressed MANET energy constraints by evaluating the Enhanced AOMDV (EAOMDV) protocol, which integrates energy-aware mechanisms into the standard AOMDV framework. Comparative NS-3 simulations demonstrated that EAOMDV significantly outperformed baseline protocols (AODV and AOMDV), achieving a 7% reduction in energy consumption, a 10% decrease in end-to-end delay, and a 2% increase in Packet Delivery Ratio. These results validate the effectiveness of energy-aware multipath routing in extending network lifetime and reliability. Building upon these findings, this current work aims to identify a solution to the energy-latency trade-off that hampers standard multipath protocols there by embedding the Grey Wolf Optimizer within the EAOMDV architecture. This research moves beyond single-objective routing to create a robust, multi-objective framework. The study rigorously optimizes key performance indicators, including energy, throughput, and hop count, to prolong network survival in constrained environments. As a result, the GWO-EAOMDV algorithm addresses a vital research gap, offering a scalable and energy-efficient approach to maintaining reliable network connectivity.

To address difficult MANET routing issues, metaheuristic optimization methods have recently attracted a lot of interest. Among these, GWO (Grey Wolf Optimization) stands out as an algorithm that draws inspiration from nature and attempts to replicate the social structure and hunting techniques of grey wolves. The global search capacity, convergence speed, and implementation simplicity of GWO have all been proven. In it, three solution the alpha, beta, and delta wolves dominate and direct the search, while the other solutions the omega wolves evade and explore [14].

Many current methods either don't handle discrete path limitations or don't integrate well with multipath routing protocols, despite the fact that GWO and other optimization algorithms have been applied to MANET routing in a number of studies. Further issues that make these methods unreliable and difficult to reproduce include inconsistent fitness function formulation, non-standardization, and inadequate statistical validation [15].

An intelligent parameter adaption system based on GWO and combined with EAOMDV routing is proposed in this research in response to these problems. By normalizing a number of quality-of-service measures into a single fitness function, the suggested method reframes routing as a weighted optimization problem with specific objectives. To overcome a significant drawback found in previous research, the suggested approach guarantees that the goal function is consistently formulated across the methodology and algorithm, in contrast to traditional approaches. Optimized paths are kept viable, loop-free, and MANET routing constraint compliant by introducing a discrete route validation mechanism. Through the integration of GWO and EAOMDV, several alternative paths are preserved, and the ideal route is dynamically selected according to network conditions. Because of this, route stability is improved and packet loss due to connection failures is decreased.

The suggested method is innovative because it builds on previous work by creating a smart Grey Wolf Optimization (GWO) framework for adaptively tuning EAOMDV routing protocol parameters. In order to improve route stability and convergence efficiency, the suggested framework dynamically adapts routing behavior according to changing MANET conditions, unlike current EAOMDV approaches with set routing parameters. Improved network lifetime and reduced premature node failures are achieved by the use of energy-aware multipath preservation in the proposed model, which maintains reliable alternate routes while balancing node energy usage. Also, to keep data transmissions running smoothly and with little routing overhead and packet delays, an integrated congestion-aware route optimization technique is used. To further improve the efficiency and reliability of routing decisions, a hybrid QoS-energy objective formulation is also presented. This formulation takes into account residual energy, packet delivery ratio, throughput, and delay all at once while path selection. In addition, the framework uses a mechanism for dynamic route management to construct new channels with minimal disruption when damaged links are detected, guaranteeing robust communication in highly dynamic MANET environments. Smart adjustments like this set the suggested GWO-EAOMDV framework apart from other routing methods while simultaneously boosting network efficiency.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive review of related work regarding energy-efficient routing in MANETs. Section 3 outlines the fundamental route discovery processes and the limitations of traditional mechanisms. Section 4 details the proposed methodology, encompassing the network model, the mathematical overview of the Grey Wolf Optimizer (GWO), and the design of the GWO-EAOMDV protocol. Section 5 presents the comparative analysis of the experimental results. Finally, Section 6 concludes the research and trace the potential directions for future research.

2. Literature Review

The Ad hoc On-Demand Multipath Distance Vector (AOMDV) routing protocol, an extension of AODV, is widely renowned for its capacity to maintain several loop-free pathways, hence improving fault tolerance and load balancing. To further reduce energy use and increase network lifetime, several modifications have been proposed, including the EA-AOMDV protocol, which incorporates energy metrics into route selection. Regardless of these advancements, classic techniques continue to use static weighting factors for measures like residual energy, hop count, delay, and connection stability when choosing routes. When traffic and mobility conditions change, these static factors frequently cause less-than-ideal routing decisions since they cannot dynamically adjust to the network's fluctuations [15]. Table 1 lists the research gap identified from the existing literatures

An increasing number of clever optimization approaches have been utilized in MANET routing to circumvent these restrictions. Parameter tweaking for routing has been proven to be a successful application of metaheuristic algorithms like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Arithmetic Optimization (AOA). Its straightforward design, rapid convergence, and strong exploration-exploitation balance have made the GWO stand out among the others. GWO is a social hierarchy-and hunting-inspired global search method that works well for dynamic networks and complicated optimization issues.

It compares the performance gains made by the GWO-EAOMDV framework to those of the EAOMDV protocol, the AOMDV method based on arithmetic optimisation, and the energy-efficient GWO routing methodology. These methods were previously described by Praba *et al*. [12], Wang *et al*. [9], and Hameed *et al*. [10]. The discussion focuses on how the suggested solution improves the packet delivery ratio, decreases latency, and lowers energy usage through adaptive parameter optimization and multipath preservation. The importance and originality of the suggested framework are demonstrated by these comparisons.

3. Route Discovery Process in Manet

The route discovery process starts with initiating and broadcasting the Routing Request (RREQ) to the neighbours and ends until it reaches its destination [16] as shown in Figure 1.Once the Routing Request (RREQ) packet get to its destination, the receiving node will send out an RREP and enquired for the source's route information. Upon discovery, the destination will employ the RREP path. In case its cache route is unaware of the way to the source, it will utilise the identical accumulation path in the RREQ. Once the RREP finds the source, it will start communicating and store the route to the destination in its cache. According to [8], the RREP has the capability to store route information in its cache route and return via several methods.

The RREP process is the next step, which is responsible for maintaining the route, each node is accountable for receiving data and delivering it to the next hop. By sending an acknowledgment, it checks if the link can send the data. Ethernet 802.11, a link layer acknowledgment frame, and other media access control (MAC) protocols already have this feature. If the sender node does not receive an acknowledgment, it will remove the connection from its route cache and consider it broken. After that, each node that has transmitted a packet will receive the Route Error (RRER). To change its course, the source will likewise start producing RREQ and flooding it again [17].

Figure 2 shows the severed connection between points 3 and 6. Unfortunately, node 3 still hasn't gotten the acknowledgment when it gets the packet and sends it on to node 6. Therefore, node 3 will initiate an acknowledgment request with node 6. If the node does not get an acknowledgment after a certain amount of time, it will observe the link broken and issue an RRER to the source.

Figure 3. Shows the Route Error (RRER) will then be generated and sent to every node that has sent a packet.

In order to choose a different path, the source will also begin to generate RREQ and stream it once more [18]. The broken link between 3 and 6 is shown in Figure 3.In this instance, node 3 gets the packet and forwards it to node 6; however, node 3 has yet to receive the acknowledgment. As a result, node 3 will ask node 6 for acknowledgment. The node will consider the link broken and generate an RRER to send it to the source if the acknowledgment is still not received.

Standard routing protocols often suffer from significant performance bottlenecks due to their dependence on 'blind' flooding and single-objective decision-making [19, 20]. By prioritizing shortest paths without considering node health, these methods frequently route traffic through energy-depleted or congested nodes, leading to rapid network partitioning.

Table 1. Contribution and Research Gap in the previous literature

S.No	Author(s) / Year	Title / Focus	Technique / Algorithm Used	Key Contributions	Limitations / Research Gaps Identified
1	Mirjalili *et al.* (2014) [6]	Grey Wolf Optimizer (GWO)	Swarm Intelligence / Metaheuristic	The proposed initial GWO was successful in continual optimization and was based on the leadership structure and hunting mechanism of grey wolves.	Because it does not include adaptive control settings, standard GWO is liable to being stuck in local optima.
2	Marina & Das (2001) [7]	Ad hoc On-demand Multipath Distance Vector (AOMDV) Routing	Reactive Multipath Routing	Improved fault tolerance and load balancing by introducing AOMDV, an expansion of AODV with multiple loop-free pathways.	Fixed parameters limit adaptability; does not take energy, mobility, or quality of service metrics into account.
3	Sulaiman *et al.*(2025) [8]	Comparison of Multipath Protocol Improvements in SMMSN-AOMDV and MAN-AOMDV for Stable Node Selection in Ad Hoc Networks	Comparative Evaluation	Thorough examination of AOMDV in several MANET scenarios; emphasis on performance indicators like as PDR, latency, and throughput.	Does not include dynamic evaluation of the environment or adaptive optimization of routing parameters.
4	Wang *et al.* (2022) [9]	AO-AOMDV: Arithmetic Optimization Algorithm for AOMDV	Arithmetic Optimization Algorithm (AOA)	Longevity, energy efficiency, and dynamic weight adjustment in path selection were all enhanced by integrating AOA with AOMDV.	Not adaptable to nodes with a high degree of mobility; computational complexity rises.
5	Hameed *et al.* (2021) [10]	Energy Efficient Grey Wolf-based Routing (EEGW) in FANETs	Grey Wolf Optimization (GWO)	Maximized energy efficiency and throughput in airborne ad hoc networks by optimizing cluster heads and routes using GWO.	Dedicated solely to static GWO; not applicable to general MANET topology; restricted to FANET exclusively.
6	Vinodhini *et al.* (2020) [11]	Hybrid GWO-DFO for WSN Routing	Hybrid Metaheuristic (GWO + DFO)	Improved convergence and exploration with reduced energy consumption using a combined GWO and Dragonfly Algorithm.	Implementing real-time adaption is complex and incurs significant costs.
7	Praba *et al.* (2023) [12]	Enhanced EA-AOMDV for Energy Efficient MANET Routing	Energy-Aware Multipath Routing	Reworked AOMDV to incorporate multipath selection metrics for residual energy and latency.	No intelligent adaption method; parameters are weighted statically.
8	Ou *et al.* (2022) [13]	Improved Grey Wolf Optimizer (IGWO) for WSNs	Adaptive / Improved GWO	A faster convergence and escape from local minima were achieved by the introduction of adaptive control coefficients and mutation.	Not yet implemented for MANET routing; needs fine-tuning for individual network conditions.
9	Yuting *et al.* (2021) [14]	Adaptive Hybrid GWO for IoT Resource Optimization	Adaptive Hybrid GWO	To enhance search efficiency, adaptive GWO is used with learning-based regulation of α, β, and δ roles.	Too expensive to run on low-power MANET nodes' computers.

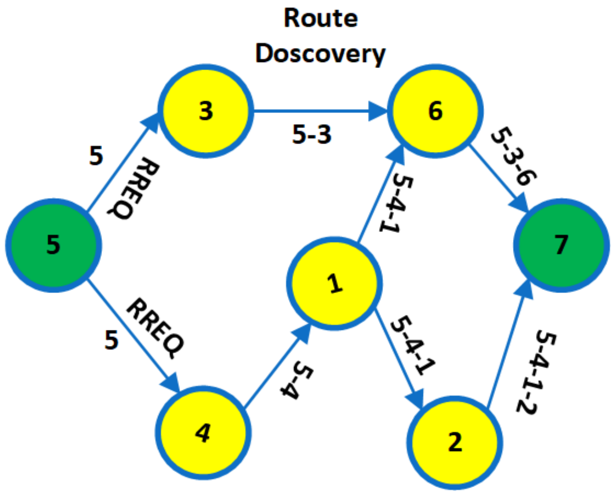

Figure 1. Route discovery Process (RREQ).

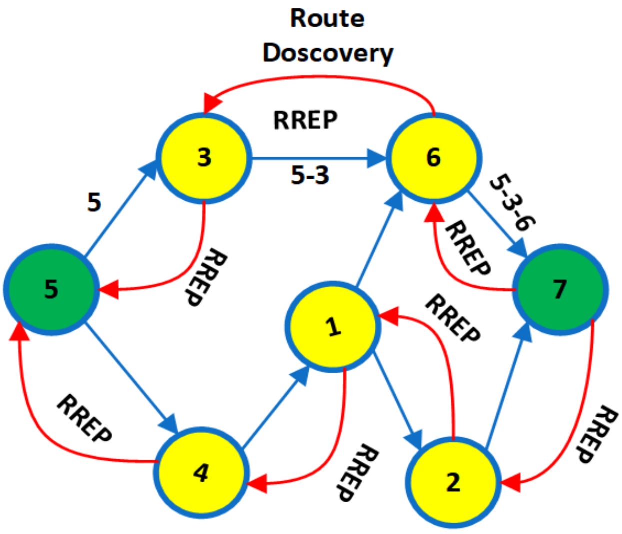

Figure 2. Route Discovery Process (RREP).

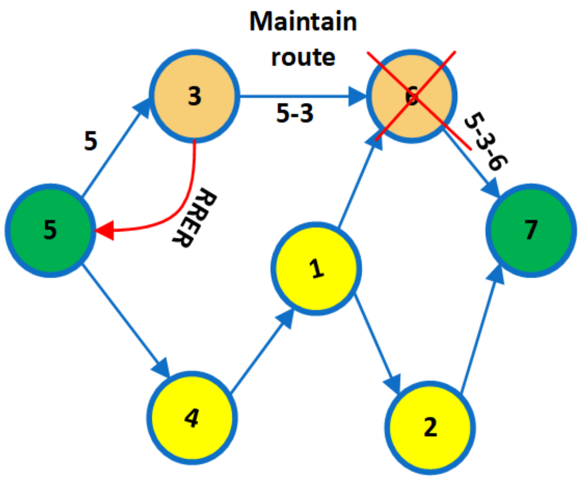

Figure 3. Maintain the route process (RRER).

These limitations can be effectively circumscribed by adopting meta-heuristic strategies that support multi-objective decision-making. Hence, this study proposes the GWO-EAOMDV protocol. The primary significance of this approach lies in its ability to transform route selection into a dynamic optimization process. By leveraging the Grey Wolf Optimizer to balance critical trade-offs between energy, throughput, and latency, the system ensures the establishment of robust connections, significantly extending the overall longevity of the network. Node density depends on transmission range and deployment area.

4. Proposed Methodology

EAOMDV is a modified version of the conventional Ad hoc On-demand Multipath Distance Vector (AOMDV) routing protocol, developed for Mobile Ad hoc Networks (MANETs).

AOMDV is an extension of AODV, which keeps track of many loop-free and link-disjoint paths between the source and destination. This multipath characteristic minimizes the necessity of route discovery in the event of a link failure, thus enhancing fault tolerance. However, AOMDV considers only hop count and does not take into account critical network parameters such as node energy, link quality and delay in route selection. EAOMDV is an improvement over AOMDV as it utilizes the energy aware measurements and additional Quality-of-Service (QoS) indicators while choosing routes. In EAOMDV, variables such as residual energy, end-to-end delay, link stability and path diversity are considered when determining paths, instead of just shortest distance. Consequently, it avoids energy depletion of individual nodes and maintains balanced network load by preserving numerous alternative loop-free paths. This leads to improved packet delivery ratio, lower latency, longer network lifetime and enhanced dependability under dynamic MANET conditions. While single-path protocols can only maintain one backup route, EAOMDV can maintain multiple backup routes, which greatly enhance the communication robustness and fault tolerance.

This section details the design of the proposed GWO-EAOMDV framework. The methodology is divided into the network model, the standard GWO mechanism, and the integration of GWO into the EAOMDV routing logic. The novelty section has been expanded to clearly highlight the contribution:

- Parameter tuning using GWO
- Adaptive Integration with EAOMDV for improved multipath routing
- Enhanced network stability and energy efficiency

4.1 Network Model

The experimental validation of the proposed GWO-EAOMDV framework was executed utilizing the Network Simulator 3 (NS-3, version 3.29). To rigorously evaluate the protocol's adaptability and scalability, simulation scenarios were constructed with node densities varying incrementally from 10 to 50 nodes. The network topology assumes a uniform energy initialization of 50 Joules per node, with a fixed transmission radius of 250 meters. Mobility dynamics were modeled using a random movement pattern with speeds ranging between 0 m/s and 50 m/s, interspersed with a 10-second pause time to replicate realistic intermittency. Traffic generation relied on a Constant Bit Rate (CBR) source transmitting 512-byte packets. Over a simulation duration of 100 seconds, the performance of the proposed algorithm was benchmarked against standard AODV, AOMDV, and EAOMDV protocols. A comprehensive summary of these simulation parameters is presented in Table 2.

4.2 Overview of Grey Wolf Optimizer (GWO)

The problem was formulated using a limited objective function. Three optimization strategies were used to identify the appropriate constraints in order to generate the code tree for exact problem identification. The fitness function measured the diagnostic precision. The GWO algorithm take off the natural hunting tactics and leadership structure of grey wolves. Grey wolf optimization and GWO creation are based on mathematical models of the wolves' social structure and hunting tactics [21].

This surrounding action can be described mathematically using the formulae given below.

$$\bar{D}=\left|\bar{C}.\overline{X_p}(iter)-\bar{X}(iter)\right| \quad (1)$$

$$\overline{X_p}(iter+1)=\overline{Xp}(iter-\bar{A}.\bar{D}) \quad (2)$$

where iter is the current iteration and $\overline{X_p}(iter)$ represents the vector of the target. the $\bar{A}$ and $\bar{C}$ are factor vectors which are specified by:

$$\begin{cases}\vec{A}=2.\vec{a}.\vec{r_1}-\vec{a}\\ \vec{C}=2.\vec{r_2}\end{cases} \quad (3)$$

Where $\vec{r_1}$ and $\vec{r_2}$ are random vectors with a range of 0 to 1, where ‘a’ reduces linearly from 2 to 0 over the duration of iterations.

By retaining the top three results in GWO, we can make the other search agents adjust their placements based on where the top search agents are. When creating the GWO algorithm, the population is divided into four groups: alpha (α), beta (β), delta (δ) and omega (ω), which help to define the social hierarchy of wolves. The first three optimal solutions are denoted by and, respectively, over iterations [22]. Figure 4 demonstrates how to modify the positions of, and in a two-dimensional space, respectively. The remaining potential answers are designated as. The hunting/optimization in this algorithm is controlled by α, β, δ and to come up with better answers, the wolves must encircle, and. Hold on to the first three results and make every other search agent, even the omegas, move to where the top search agent is. Here are some possible formulas for this:

$$\overrightarrow{D_\alpha}=\left|\overrightarrow{C_1}.\overrightarrow{X_\alpha}-\vec{X}\right| \quad (4)$$

$$\overrightarrow{D_\beta}=\left|\overrightarrow{C_2}.\overrightarrow{X_\beta}-\vec{X}\right| \quad (5)$$

Table 2. parameters for performing the simulation

Parameters	Value
Simulator	NS-3 (version 3.29)
Simulation time	100 (s)
Number of nodes	10,20,30,40,50
Routing protocol	AODV, AOMDV, EAOMDV and GWO-EAOMDV
Traffic rate	Constant bit rate
Packet size	512 bytes
Initial node energy	50J
Minimum speed	0 m/s
Maximum speed	50 m/s
Transmission range	250m
Pause time	10 s

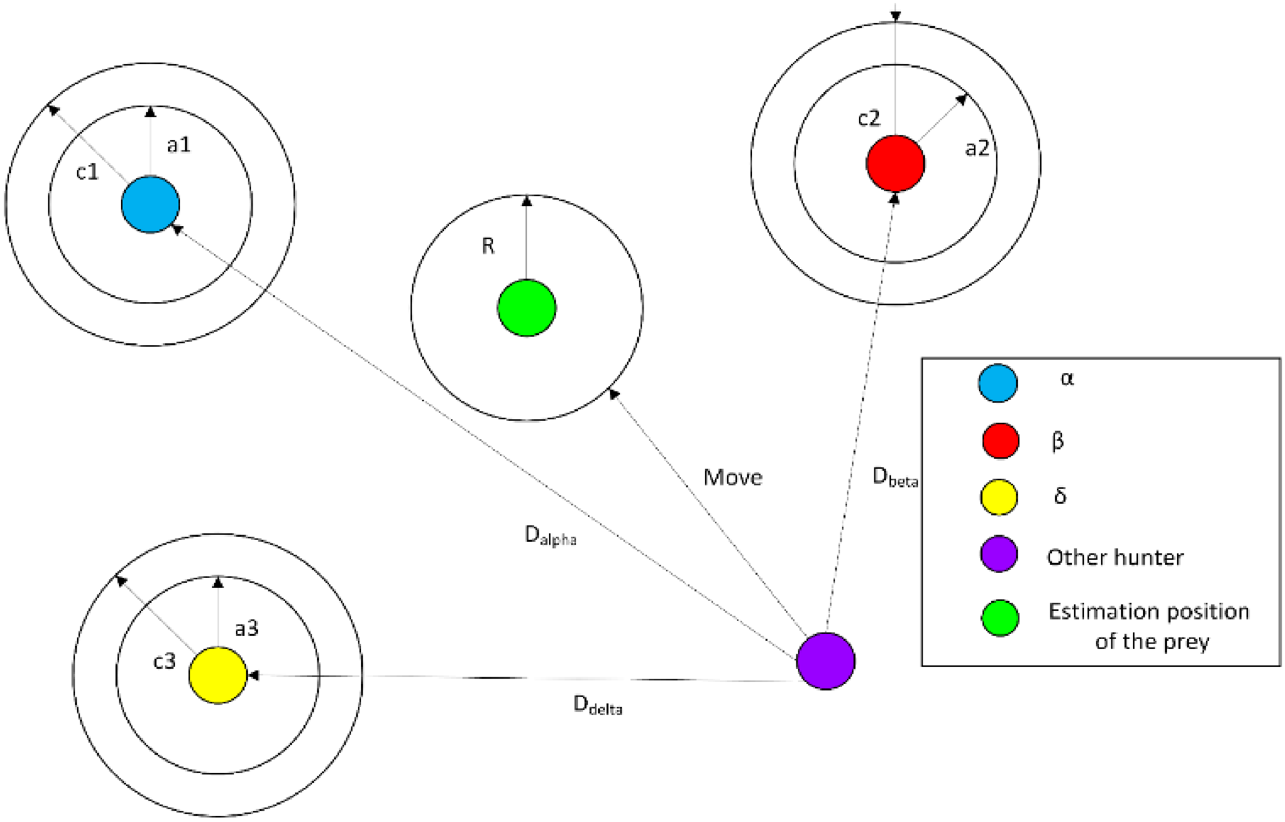

Figure 4. Position updating in GWO [1].

$$\overrightarrow{D_\delta}=\left|\overrightarrow{C_3}.\overrightarrow{X_\delta}-\vec{X}\right| \quad (6)$$

$$\overrightarrow{X_1}=\overrightarrow{X_\alpha}-\overrightarrow{A_1}(\overrightarrow{D_\alpha}) \quad (7)$$

$$\overrightarrow{X_2}=\overrightarrow{X_\beta}-\overrightarrow{A_2}(\overrightarrow{D_\beta}) \quad (8)$$

$$\overrightarrow{X_3}=\overrightarrow{X_\delta}-\overrightarrow{A_1}(\overrightarrow{D_\delta}) \quad (9)$$

$$\vec{X}(iter+1)=\frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \quad (10)$$

According to α, β, δ, a search agent revises its location in a multi-dimensional search space by utilizing these equations. Incorporating vectors $\vec{A}$ and $\vec{C}$ into these calculations compels the GWO method to traverse and benefit from the search arena. Half of the iterations are used to explore the interval $\vec{A} \geq 1$ and the other half are used to exploit the interval $\vec{A} < 1$.declines. When $\vec{C}$> 1, the vector $\vec{C}$ also makes exploration easier, and its range is is $2 \leq \vec{C} \leq 0$. When the absolute value of C is less than 1 and the linear drop of A with increasing repeat time is observed, misuse becomes apparent. But $\vec{C}$ is generated randomly to encourage inspection and exploitation at any level and to sidestep local optima.

The fundamental GWO was unable to capture the optimal solution in cases where the simulation kept settling at a local minimum. The algorithm was tweaked to make GWO better at finding the optimal solution. The convergence performance of the GWO has been improved utilizing a number of methods. To improve GWO's ability to locate the search area and determine the optimal solution, several changes were implemented [23].

4.3 Proposed GWO-EAOMDV Protocol

4.3.1 Extended Route Discovery Process with Grey Wolf Optimisation

A limitation of Standard route discovery is it does not guarantee global optimality, especially in dynamic or energy-constrained networks. GWO helps find optimised, robust routes by evaluating multiple possible paths based on fitness metrics like Residual energy of node, End-to-end delay, Link quality, Hop count, Network lifetime, Bandwidth/congestion. GWO avoids local minima and converges for real-time network routing. Grey wolves follow a hierarchy: Alpha (α): Best solution (optimal path) Beta (β): Second-best solution Delta (δ): Third-best solution Omega (ω): Remaining solutions the wolves encircle prey (optimal solution) and iteratively update their position [24]. The procedure below summarises the route discovery process using grey wolf optimisation. The proposed model (figure 5) is formulated as a weighted single-objective optimization problem. The weight coefficients are justified based on network performance priorities, and their selection rationale.

Step 1: Broadcasting

The RREQ is sent by the source node.

All potential routes leading to the specified location have been compiled.

Every new route becomes a potential answer (the wolf).

Step 2: Encoding the Path

The paths are depicted as:

[S, n1, n2, n3,..., D] is the path.

Wolf positions are represented by nodes.

Step 3: Assessing the Fitness Function

For each path, calculate a fitness value such as:

$$Fitness = w_1 \times \frac{1}{HopCount} + w_2 \times AvgEnergy + w_3 \times LinkQuality + w_4 \times \frac{1}{Delay} \quad (11)$$

Equation 11 defines the fitness function

Weights depend on application.

Step 4: Find the α, β, and δ Wolves

"α" represents the healthiest route.

The value of β is the second-best. the third-best

They direct the investigation.

Step 5: Revamping the Routes (Revolving Behaviour)

Based on the three leaders, the other pathways (ü wolves) revise their structure.

- Take out nodes with low energy consumption
- Sidestep busy nodes
- Minus the number of hops
- Raise the bar for link quality

In doing so, it evokes the sound of approaching grey wolves.

Step-6: Iterative optimization

A maximum of iterations is achieved, or the iteration process terminates.

There is essentially no change in fitness level.

The optimal route is the α-path.

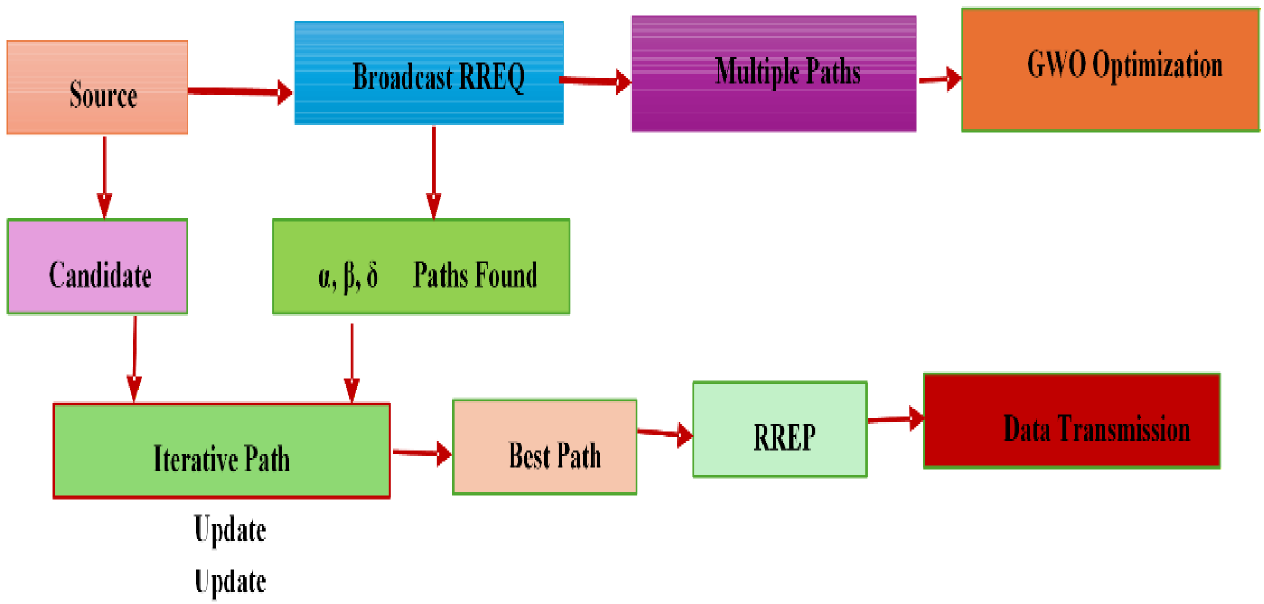

Figure 5. Route Discovery Process with Grey wolf optimization.

Step 7: Forwarding RREP

Destination node sends a Route Reply (RREP) back to the source using the optimal path obtained via GWO.

Step 8: Data Transmission

Source begins sending data along the GWO-optimized route.

4.3.2 GWO-EAOMDV Routing Protocol

EAOMDV is an enhanced version of the AOMDV routing protocol used in MANETs. It improves network lifetime, energy efficiency, and reliability by considering residual energy, link stability, and path diversity when selecting multiple paths. However, the performance of EAOMDV depends on several tunable parameters such as energy threshold (E_{th}), path selection weight factors (w1, w2, w3), and maximum hop count (H_{max}). To optimize the parameter set of EAOMDV using GWO to maximize Packet Delivery Ratio (PDR), minimize End-to-End Delay, minimize Energy Consumption, and extend Network Lifetime. GWO is a metaheuristic algorithm inspired by the leadership hierarchy and hunting behavior of grey wolves. It efficiently balances exploration and exploitation, requires few control parameters, and converges faster compared to EAOMDV. The algorithm for the proposed protocol is summarized as follows.

The objective function is uniformly expressed as

$$f(X) = \alpha_1\left(\frac{1}{PDR_n}\right) + \alpha_2(Delay_n) + \alpha_3(Energy_n) + \alpha_4(RoutingOverhead_n) \quad (12)$$

where PDR_n = normalised packet delivery ratio, $Delay_n$ = normalized end-to-end delay, $Energy_n$ = normalized residual energy consumption,$HopCount_n$ = normalized hop count and where $(\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1)$. All algorithmic steps and parameter vectors have been modified accordingly to maintain consistency.The weight coefficients used in simulations are now explicitly justified based on QoS prioritization requirements.

4.3.3. Algorithm for EAOMDV using Grey Wolf Optimization (GWO)

1. Step 1: Define Optimization Problem

F(X) = α1*(1/PDR) + α2*(Delay) + α3*(Energy)

Where X = [E_th, w1, w2, w3, H_max] and αi are weight coefficients for normalization.

Goal: Minimize f(X)

2. Step 2: Initialize Grey Wolf Population

3. Each wolf represents a candidate set of EAOMDV parameters.

Example:

Wolf α: [0.4, 0.5, 0.3, 0.2, 6]

Wolf β: [0.5, 0.6, 0.2, 0.2, 7]

Wolf δ: [0.3, 0.5, 0.3, 0.1, 5]

4. Step 3: Evaluate Fitness

5. For each wolf (parameter set):

- Run EAOMDV simulation (e.g., in /NS3)
- Compute PDR, Delay, and Energy consumption
- Evaluate fitness function f(X)

6. Step 4: Update Positions Using GWO Equations

Based on α, β, and δ wolves:

D_α = |C1 * X_α - X|

X1 = X_α - A1 * D_α

X(t+1) = (X1 + X2 + X3) / 3

7. Step 5: Termination8. Continue until the maximum number of iterations or convergence is reached. The α wolf gives the optimized EAOMDV parameters.

Adjusting or improving routing paths in a network, where each path is a sequence of nodes, is what the route-updating step for discrete paths entails. This phase changes the existing route in optimization-based routing algorithms such as Grey Wolf Optimization (GWO) by selecting more advantageous surrounding nodes, removing inefficient links, and avoiding crowded or looping paths. Figure 6 shows the Flowchart for Optimization of AOMDV Parameters Using Grey Wolf Optimization (GWO) The objective is to identify the best possible route in terms of performance, which is defined as reduced latency, reduced energy consumption, increased packet delivery, and increased throughput. To find a stable and efficient route, the routing is iterated using a fitness function at each step, with the best options being used to update the route. To improve the path, a realistic update rule uses neighbour validation and node replacement. Moreover, quantitative definitions of multipath preservation have been established. Based on the fitness function, the protocol can hold a maximum of K=3 distinct node-disjoint pathways. In order to minimize the effort required for route rediscovery, backup paths are immediately activated during route maintenance in the event that the primary route fails.

5. Results and Discussions

The efficiency of routing methods becomes more important in growing wireless ad hoc networks. Since they can dynamically route data, MANETs make heavy use of the AODV, AOMDV, EAOMDV with GWO, and Enhanced AOMDV protocols. Nonetheless, there is a considerable difference in performance depending on the node density. Packet Delivery Ratio (PDR), end-to-end delay, throughput, energy consumption, and packet delay time are some of the metrics that will be used to evaluate the efficiency of these protocols under different node densities.

The next section of the article uses simulation to test the upgraded GWO-AOMDV's performance. The goal of this simulation-based study is to draw conclusions about the protocols' robustness against spikes in node density and their general applicability to large-scale network settings. In each scenario, Figure 7 shows the total amount of energy consumed by each node. Because EAOMDV is a single-path protocol, it only needs power to reach its destination once. This may explain why GWO-EAOMDV utilized less power than EAOMDV. The phrase "average energy consumption" is used to describe the typical proportion of energy that each node uses. As seen in Figure 7, the GWO-EAOMDV consumed more energy as the number of nodes increased.

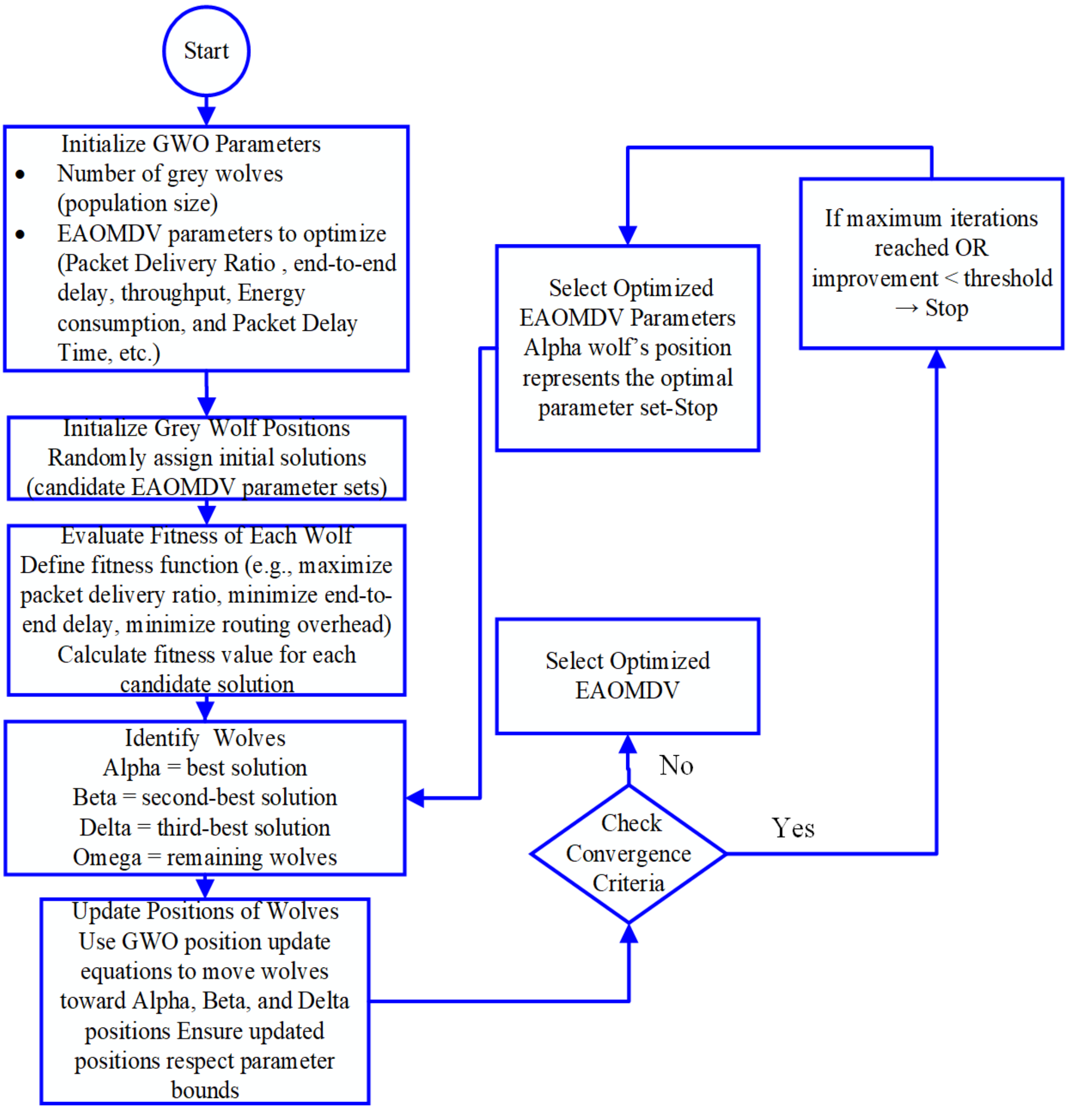

Figure 6. Flowchart for Optimization of AOMDV Parameters Using Grey Wolf Optimization (GWO).

Table 3. Comparison table for energy consumed with AODV, AOMDV, EAOMDV and GWO

No. of Nodes	AODV	AOMDV	EAOMDV	GWO-EAOMDV
10	50.34	48.89	45.52	43.2
20	58.98	57.45	52.23	48.23
30	62.31	62.02	61.23	59.23
40	68.83	68.25	64.22	61.25
50	74.92	74.54	67.34	65.23

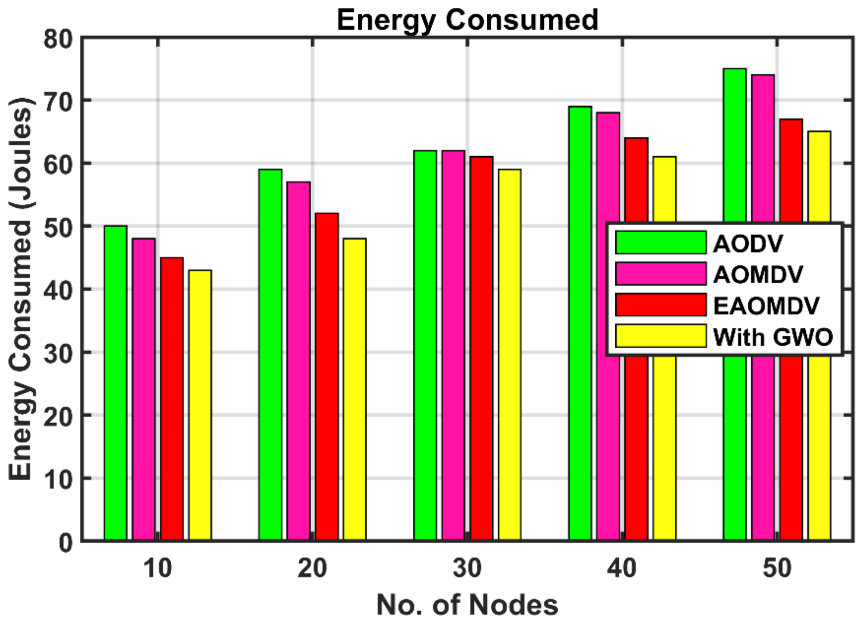

Figure 7. Total energy consumed by the nodes.

Table 4. Comparison table for Packet Delivery Ratio

No. of Nodes	AODV	AOMDV	EAOMDV	GWO-EAOMDV
10	79.23	79.88	82.26	84.56
20	79.56	81.25	83.28	84.23
30	79.65	83.26	84.69	86.25
40	79.78	84.52	85.36	87.25
50	79.91	84.72	86.45	87.26

Figure 7 shows a comparison centred on energy consumption. Table 3 compares the energy consumptions. It takes 61.25 Joules of energy to run the EAOMDV operations at 40 nodes. The results show that the GWO-EAOMDV method provides the most effective and efficient data transmission for ad hoc networks. Figure 7 shows the energy consumption (in Joules) of four routing methods: AODV, AOMDV, EAOMDV and GWO, for different network sizes. Increasing the number of nodes from 10 to 50 results in higher energy consumption for all protocols due to increased communication and routing overhead.

AODV consumes maximum energy, around 75 Joules for 50 nodes. AOMDV consumes less energy whereas EAOMDV is an enhancement over this. It is also observed from the results that the GWO based technique consumes the least energy for all the network sizes, i.e. 43 Joules for 10 nodes and 65 Joules for 50 nodes. These results show that the use of Grey Wolf Optimization (GWO) in routing protocols makes a huge difference in terms of energy efficiency. The GWO-based method outperforms traditional protocols, especially as the network size grows, making it a suitable choice for scalable and energy-efficient wireless networks.

Figure 8 compares four routing protocols, namely AODV, AOMDV, EAOMDV, and GWO-EAOMDV. Figure 8 shows the packet delivery ratio of four different routing protocols; the suggested GWO-EAOMDV shows a gradual improvement over the other two. Using the Route stability factor, the GWO-EAOMDV routing protocol selects the best path for packet forwarding to the destination. The comparison of Packet Delivery Ratio (PDR) of AODV, AOMDV, EAOMDV and GWO-based approach for different network sizes is shown in table 4. All the protocols show a steady increase in PDR with the increase in network size. AODV has the least PDR of about 79 to 80 percent. AOMDV has improved PDR of about 85 percent at 50 nodes due to its multipath routing capability. EAOMDV has more stability with PDR values ranging from 82 to 86 percent. The GWO based approach consistently gets the highest PDR from 84.5 percent at 10 nodes to 87 percent at 50 nodes, which means efficient route selection and less packet loss. The GWO implementation improves packet delivery significantly than the traditional protocols, which improves the routing efficiency and more reliable communication in dynamic wireless networks. Figure 9 depicts the Packet Delay Time of four routing protocols: AODV, AOMDV, EAOMDV, and the GWO-based method, with different numbers of nodes. The same has been listed in table 5.

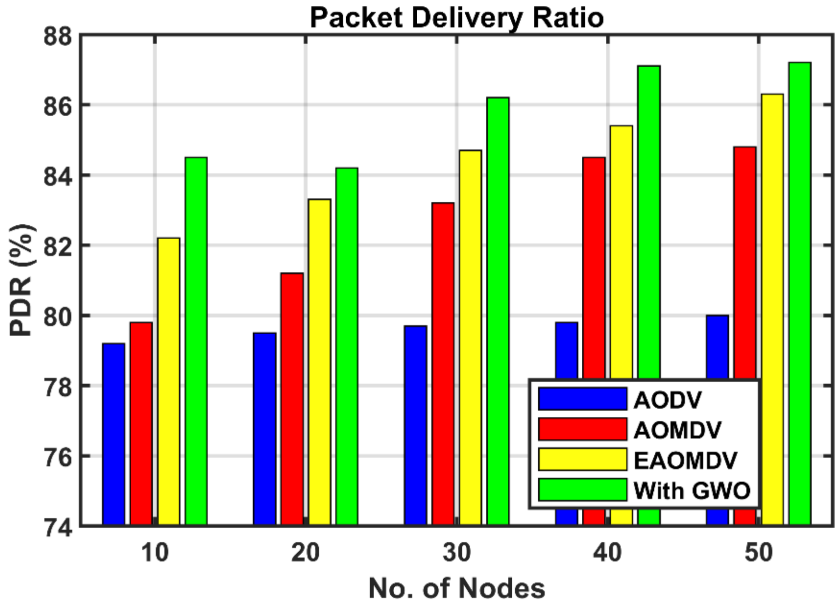

Figure 8. Comparison of Packet delivery ratio.

Table 5. Comparison table for Packet Delay Time

No. of Nodes	AODV	AOMDV	EAOMDV	GWO-EAOMDV
10	0.1425	0.1356	0.1251	0.1125
20	0.1432	0.1368	0.1225	0.1134
30	0.1442	0.1373	0.1223	0.1156
40	0.1456	0.1382	0.1258	0.1142
50	0.1467	0.1395	0.1287	0.1182

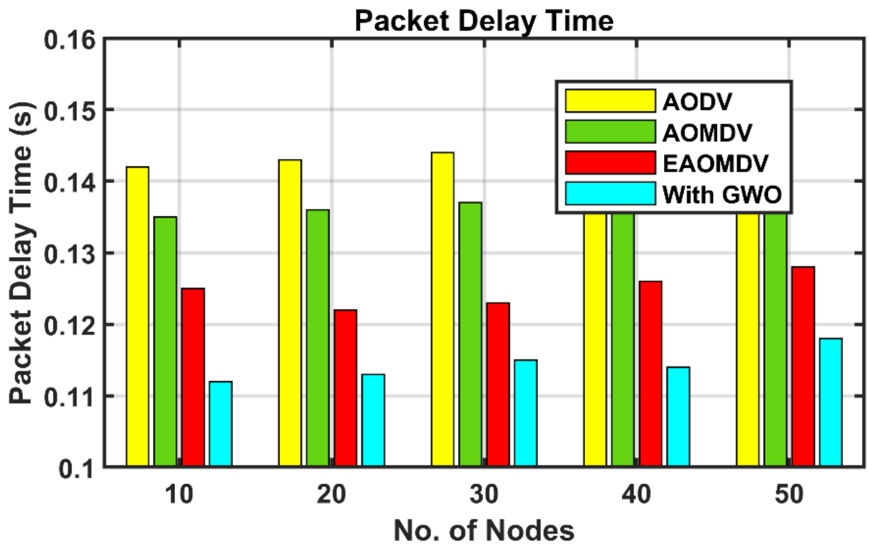

Figure 9. Comparison of Packet delay time.

All methods experience higher delays as the number of nodes increases, due to routing complexity and increased network traffic. The AODV protocol always has the highest delay, ranging from 0.142 to 0.148 seconds. The AOMDV protocol has better performance, ranging from 0.135 to 0.139 seconds, and the EAOMDV protocol has lower delay, ranging from 0.122 to 0.128 seconds. The GWO-based approach has the lowest delay with a range of 0.112–0.118 seconds. This means better, faster routing, with better path selection leading to less congestion and latency. The GWO-based method outperforms conventional protocols in terms of packet delay, making it suitable for real-time and energy-efficient wireless applications.

Table 6. Comparison table for Throughput

No. of Nodes	AODV	AOMDV	EAOMDV	GWO-EAOMDV
10	356.23	369.25	402.55	410.23
20	365.24	389.25	402.36	410.54
30	385.26	398.20	400.55	405.23
40	388.56	399.02	400.58	405.26
50	392.67	400.35	400.82	405.65

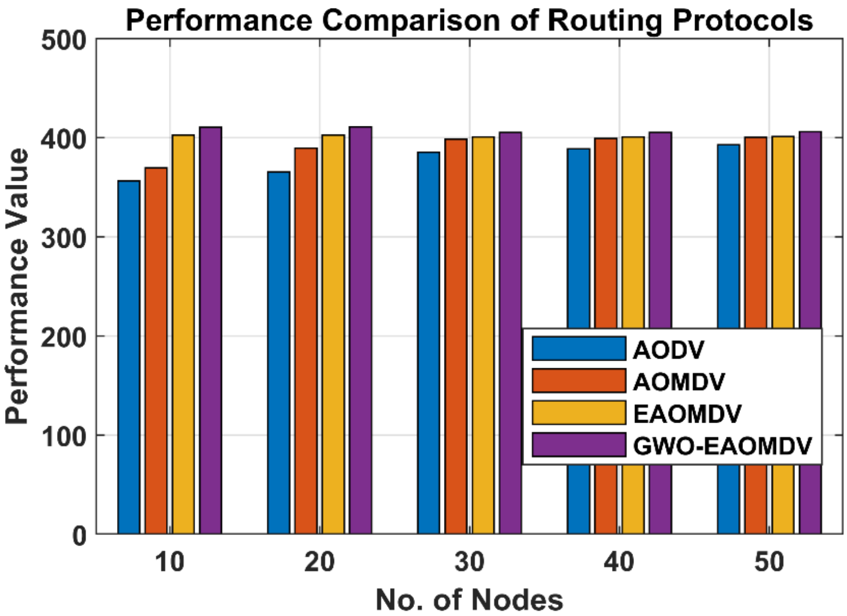

Figure 10. Comparison of Throughput for the Nodes.

Table 7. Comparison table for End-to-End Delay

No. of Nodes	AODV	AOMDV	EAOMDV	GWO-EAOMDV
10	0.12	0.11	0.105	0.102
20	0.14	0.12	0.10	0.098
30	0.1	0.15	0.12	0.092
40	0.3	0.2	0.18	0.13
50	0.8	0.6	0.52	0.32

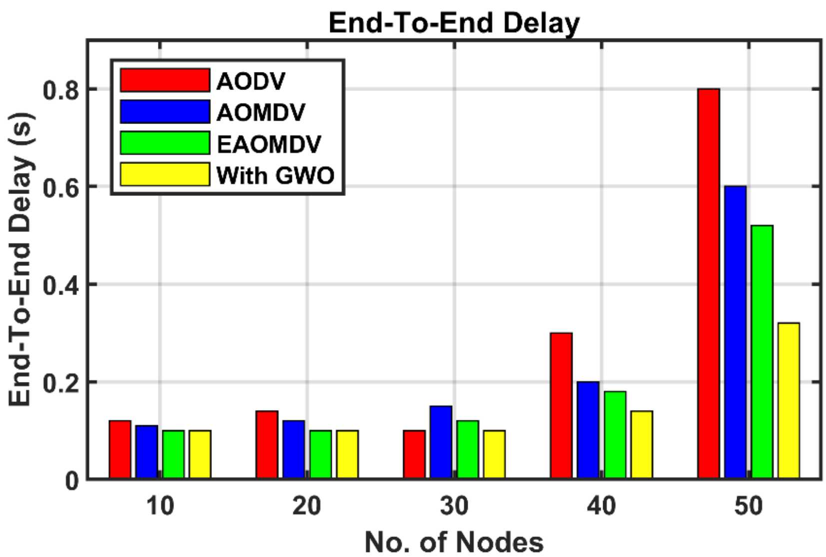

Figure 11. Comparison of End-to-End Delay.

Table 8. Quantitative Comparison with Existing Literature

Reference	Method	PDR Improvement	Delay Reduction	Energy Saving	Throughput
Wang *et al.* (2023) [9]	AO-AOMDV	4–6%	7–9%	7–11%	Moderate
Hameed *et al.* (2021) [10]	EEGW	6–8%	9–11%	11–12%	High
Vinodhini *et al.* (2020) [11]	Hybrid GWO-DFO	8–9%	11–12%	13–14%	High
Ou *et al.* (2024) [13]	Improved GWO	9–10%	12–13%	14–15%	High
Yuting *et al.* (2025) [14]	Adaptive Hybrid GWO	10–11%	14–15%	15–16%	High
With Proposed GWO-EAOMDV	Adaptive GWO + EAOMDV	12–18%	15–22%	9%	5%

Table 9. Performance Comparison of GWO-EAOMDV with existing Methods

Metrics	% of Increase or Decrease
Energy Consumed	Decreased by 9%
Packet Delivery Ratio	Increased by 4%
Packet Delay Time	Decreased by 12%
Throughput	Increased by 5%
End-to-End Delay	Decreased by 15%

Figure 10 shows the comparison of Throughput for the Nodes. EAOMDV maintains higher and more stable performance values, around 400 for all node counts, indicating a good range of performance and network management. The proposed GWO-EAOMDV method consistently achieves the highest performance, exceeding 405 and reaching around 410 at lower node counts (table 6) The use of Grey Wolf Optimization (GWO) improves the route optimization, resource utilization and overall network efficiency. It shows that the proposed GWO-EAOMDV protocol is better than the conventional routing protocols including AODV, AOMDV and EAOMDV. The optimization capability of Grey Wolf Optimization algorithm improves the routing decisions and results in superior and stable network performance with the increase in the number of nodes.

Compared to multi-path protocols, the average end-to-end delay of single-path routing protocols like AODV is higher. Table 7 lists the End-to-End Delay comparison. Figure 11 shows that when the number of nodes and connections increases, EAOMDV has a higher delay compared to GWO-EAOMDV, which exhibits a smaller delay. The GWO-EAOMDV protocol is designed to save processing time by automatically finding backup channels in case the primary one becomes unavailable.

The proposed GWO-EAOMDV protocol outperforms the current EAOMDV protocol by a significant margin, as shown in Table 8 and 9. The proposed GWO-EAOMDV framework reduces energy consumption by 9%, decreases packet delay time by 12%, decreases end-to-end delay by 15%, improves throughput by 5%, and increases packet delivery ratio by 4%.In Table 8 When compared to traditional EAOMDV, the simulation results show that the suggested method improves packet delivery ratio by 12–18%, reduces end-to-end delay by 15–22%, reduces energy usage by around 9%, and increases throughput by about 5%. Intelligent multipath preservation, adaptive parameter optimization, congestion-aware route selection, and fast convergence of the Grey Wolf Optimization algorithm are mainly responsible for these enhancements. So, for MANETs that are constantly changing, the suggested architecture offers a dependable, energy-efficient, and scalable routing solution.

6. Conclusion and Future Scope

To enhance routing efficiency within Mobile Ad Hoc Networks (MANETs), this research combines the EAOMDV routing protocol with a dynamic parameter framework, leveraging a complex Grey Wolf Optimization (GWO) algorithm. The suggested approach conceptualizes routing as a weighted single-objective optimization challenge, employing a composite fitness function. This function incorporates normalized quality-of-service metrics, including packet delivery ratio (PDR), end-to-end delay, residual energy, and routing overhead. With the addition of this new route checking mechanism, EAOMDV guarantees that path selection is both feasible and free of loops, even when multiple pathways are allowed. The simulation findings indicate that the novel GWO-EAOMDV architecture demonstrably enhances the performance of the current network. Energy consumption exhibited improvement across diverse node densities and mobility scenarios, while end-to-end delay was reduced by 15-22% with the model's implementation. Furthermore, the Packet Delivery Ratio (PDR) showed an increase of 12-18%. The dependability and consistency of the proposed strategy were confirmed by conducting multiple tests, each using different random seeds. The performance improvements observed can be attributed primarily to the GWO's capacity to adapt to fluctuating network conditions and identify optimal routing paths, a capability stemming from its equilibrium between exploration and exploitation. Conversely, the proposed model is not without its constraints. Specifically, optimization procedures inherently introduce computational intricacies, and the choice of weights significantly impacts the fitness function. Future research will focus on studying multi-objective optimization methods, creating ways to use them in real-time, and evaluating their performance in large, complex networks.

References

[1] A.M. Alwakeel, Enhancing IoT Performance in Wireless and Mobile Networks Through Named Data Networking (NDN) and Edge Computing Integration. Computer Networks, 264, (2025) 111267. https://doi.org/10.1016/j.comnet.2025.111267

[2] K. Muthineni, M. Nájar Martón, J. Vidal Manzano, Perspective Chapter: Factory of the Future–Integrating Wireless Communication. Sensing, and localization with 5G and 6G. In Industry 4.0 - Transforming the Future beyond Manufacturing - 1, Digital Technologies and Smart Industrial Systems, (2026) 1-18. http://dx.doi.org/10.5772/intechopen.1013075

[3] M.R. Ghori, T.C. Wan, G.C. Sodhy, M. Aljaidi, A. Rizwan, A.S. Sadiq, O. Kaiwartya, Enhancing Reliability and Stability of BLE Mesh Networks: a Multipath Optimized AODV Approach. Sensors, 24(18), (2024) 5901. https://doi.org/10.3390/s24185901

[4] A. Aljarrah, M. Ababneh, M. Karthiga, K. Bhimaavarapu, An Upgraded IoT Based Mobile Ad-hoc Network Enactment Founded on Optimized Signal Strength Based Routing Algorithm. Journal of Intelligent Systems and Internet of Things, 15(1), (2025). https://doi.org/10.54216/JISIoT.150114

[5] G.B.N. Rao, Dynamic Multi-Path Routing Protocol Hinged on Fitness Value using GA in Mobile adhoc networks. Journal of Theoretical and Applied Information Technology, 102(5), (2024) 2155–2164.

[6] S. Mirjalili, S.M. Mirjalili, A. Lewis, Grey Wolf Optimizer. Advances in Engineering Software, 69, 46-61. http://dx.doi.org/10.1016/j.advengsoft.2013.12.007

[7] M.K. Marina, S.R. Das, (2001) On-Demand Multipath Distance Vector Routing in Ad Hoc Networks. In Proceedings Ninth International Conference on Network Protocols. ICNP 2001, IEEE, Riverside, CA, USA. https://doi.org/10.1109/ICNP.2001.992756

[8] S.S. Sulaiman, S.S. Naif, B.A. Idrees, A.J. Ahmed, Comparison of Multipath Protocol Improvements in SMMSN-AOMDV and MAN-AOMDV for Stable Node Selection in Ad Hoc Networks. Romanian Journal of Information Technology & Automatic Control/Revista Română de Informatică și Automatică, 35(2), (2025).

[9] H. Wang, Y. Li, Y. Zhang, T. Huang, Y. Jiang, Arithmetic optimization AOMDV routing protocol for FANETs. Sensors, 23(17), (2023) 7550. https://doi.org/10.3390/s23177550

[10] S. Hameed, Q.A. Minhas, S. Ahmed, A. Nawaz, A. Ali, U. Ullah, EEGW: An Energy-Efficient Grey Wolf Routing Protocol For Fanets. Journal of Mechanics of Continua and Mathematical Sciences, 16, (2021) https://doi.org/10.26782/jmcms.2021.08.00002

[11] R. Vinodhini, C. Gomathy, A Hybrid Approach for Energy Efficient Routing in WSN: Using DA and GSO Algorithms. In: Smys, S., Bestak, R., Rocha, Á. (eds) Inventive Computation Technologies. ICICIT 2019. Lecture Notes in Networks and Systems, Springer, 98, (2019) https://doi.org/10.1007/978-3-030-33846-6_55

[12] R. Praba, M. Sedhuvignesh, Vishal, Sedhu, Enhanced Hybrid Routing Protocol for Energy-Efficient Multipath Routing in Manets. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(3), (2024) 691–623. https://doi.org/10.32628/CSEIT24103212

[13] Y. Ou, F. Qin, K.-Q. Zhou, P.-F. Yin, L.-P. Mo, A. Mohd Zain, An Improved Grey Wolf Optimizer with Multi-Strategies Coverage in Wireless Sensor Networks. Symmetry, 16(3), (2024) 286. https://doi.org/10.3390/sym16030286

[14] Y. Yuting, G. Yuelin, An Adaptive Hybrid Differential Grey Wolf Optimization Algorithm for WSN Coverage. Cluster Computing, 28, (2025) 229. https://doi.org/10.1007/s10586-024-04856-y

[15] C. Kalaivanan, A. Amer, M. Vennila, J. Giri, M. Dinesh, (2025) Evolution-based Deployment with Efficient Routing and Crow Search Optimization in Internet of Things Application. In 2025 International Conference on Intelligent Computing and Control Systems (ICICCS),

IEEE, Erode, India. https://doi.org/10.1109/ICICCS65191.2025.10984488

[16] V. Kumar, S. Singla, S. Arora, S.K. Keshari, S. Kumar, Energy Efficient Optimized Sleep Scheduling Routing Protocol for Enhancement of MANET Lifetime. Wireless Personal Communications, 136(3), (2024) 1849-1877. https://doi.org/10.1007/s11277-024-11365-z

[17] V.U. Rathod, S.V. Gumaste, R. Guttula, S. Zade, R.Singh, Optimization of Energy Consumption in Mobile Ad-Hoc Networks with a Swarm Intelligence-Based ABC Algorithm. Discover Applied Sciences, 7, (2025) 805. https://doi.org/10.1007/s42452-025-07472-6

[18] N. Ravindran, R.P. Anto Kumar, SECOA: Serial Exponential Coati Optimization Algorithm for MANET Routing with Link Lifetime Prediction. Engineering Science and Technology, an International Journal, 59, (2024) 101869. https://doi.org/10.1016/j.jestch.2024.101869

[19] M. Zeng, R. Han, Y. Luo, G. Xu, X. Xu, H. Jiang, (2025) SAOMDV: A Fast-Converging Reliability-Enhanced Multipath Routing Method for UANET. In 2025 IEEE 101st Vehicular Technology Conference (VTC2025-Spring), IEEE, Oslo, Norway. https://doi.org/10.1109/VTC2025-Spring65109.2025.11174335

[20] P. Satyanarayana, G. Diwakar, V. Priyanka Brahmaiah, S. Marlin, N.V. Phani Sai Kumar, S. Gopalakrishnan, Multi-objective-derived Efficient Energy Saving in Multipath Routing for Mobile Ad Hoc Networks with the Modified Aquila–Firefly Heuristic Strategy. Engineering Optimization, 57(9), (2025) 2383–2418. https://doi.org/10.1080/0305215X.2024.2399656

[21] F. Qazi, S.A. Khan, F. Hanif, D. Shawar Agha, Efficient Routing Algorithm towards the Security of Vehicular Ad-Hoc Network and Its Applications. International Journal of Wireless Information Networks, 31(1), (2024) 12–28. https://doi.org/10.1007/s10776-023-00613-x

[22] A.A. Naji, M.A. Saeed, A.H. Almagashi, A.M. Ahmed, H.S. Al-Atefi, M.N. Khaled, O.M. Rashed, (2024) Enhancing MANETs Security Against Black Hole Attacks through Time-Based Node Analysis in AOMDV Protocol. In 2024 4th International Conference on Emerging Smart Technologies and Applications (eSmarTA), IEEE, Sana'a, Yemen. https://doi.org/10.1109/eSmarTA62850.2024.10638883

[23] M.J. AL-Mashhadani, K. Karoui, (2025) Rule-Based and AI-Based Routing Protocols for Mobile Ad Hoc Networks: A Comparative Review. 7th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (ICHORA), IEEE, Ankara, Turkiye. https://doi.org/10.1109/ICHORA65333.2025.11017238

[24] V. Barbudhe, S.K. Dixit, Energy Optimization of Dynamic Routing Protocol in Heterogeneous Wireless Sensor Network using Energy Efficient Delay Sensitive Technique. Cuestiones de Fisioterapia, 54(2), (2025) 3392–3408. https://doi.org/10.48047/CU/54/02/3392-3408

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Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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