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ENHANCING QOS-BASED ROUTING IN MANETS THROUGH HYBRIDIZATION OF GREYWOLF OPTIMIZATION AND ANT COLONY OPTIMIZATION ALGORITHMS

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Abstract: Mobile Ad Hoc Networks (MANETs) face significant challenges in achieving Quality of Service (QoS) in routing due to their dynamic and decentralized nature. This paper proposes a novel approach to enhance QoS-based routing in MANETs by introducing a hybrid optimization algorithm that combines the strengths of Greywolf Optimization and Ant Colony Optimization. The hybrid algorithm is designed to address the limitations of existing algorithms, including Artificial Bee Colony, Ant Colony Optimization, and Greywolf Optimization. Through comprehensive simulations and performance evaluations, this research analyze the effectiveness of the proposed hybrid algorithm in improving QoS metrics compared to traditional and state-of-the-art routing algorithms. The results indicate promising enhancements in terms of reliability, latency, and throughput, highlighting the potential of the hybrid approach for robust QoS-aware routing in MANETs.

Keywords: Mobile Ad Hoc Networks, Quality of Service, QoS-Based Routing, Greywolf Optimization Algorithm, Ant Colony Optimization Algorithm, Artificial Bee Colony Algorithm

I.INTRODUCTION

Mobile Ad Hoc Networks (MANETs) have emerged as a crucial component in modern communication systems, enabling wireless communication among nodes without the need for a fixed infrastructure. The dynamic and decentralized nature of MANETs poses significant challenges to efficient routing, making Quality of Service (QoS) an essential consideration for applications ranging from military and disaster response to sensor networks and multimedia streaming [1]. In this context, the development of robust QoS-based routing protocols is imperative to ensure reliable and efficient data transmission. MANETs operate in dynamic environments where nodes may join or leave the network unpredictably. This inherent dynamism poses challenges for traditional routing algorithms, as they are often designed for static or less dynamic networks. QoS requirements, including reliability, latency, and throughput, become crucial in applications such as video conferencing, multimedia streaming, and critical data transmission [2]. The need for effective QoS-based routing in MANETs arises from the increasing demand for reliable and efficient communication in various domains. The unpredictable and resource-constrained nature of MANETs requires innovative approaches to address the unique challenges associated with routing in such networks. The motivation for this research lies in the quest for an optimized and adaptive routing protocol that can dynamically adjust to the changing conditions of MANETs. The primary objectives of this research are twofold: first, to enhance QoS-based routing in MANETs, and second, to compare the performance of a novel hybrid optimization algorithm with existing state-of-the-art algorithms. By achieving these objectives, we aim to contribute to the development of more robust and efficient routing protocols for MANETs, thereby improving the overall performance and reliability of communication in dynamic and resource-constrained environments. This paper introduces a hybrid optimization algorithm that combines the strengths of Greywolf Optimization and Ant Colony Optimization, aiming to overcome the limitations of existing QoS-aware routing algorithms. The subsequent sections delve into the literature review, methodology, algorithm design, performance evaluation, results, and discussion, ultimately providing insights into the effectiveness of the proposed hybrid approach in enhancing QoS-based routing in MANETs.

Importance of Quality of Service (QoS) in MANETs:

Quality of Service (QoS) plays a pivotal role in Mobile Ad Hoc Networks (MANETs) due to the unique characteristics and challenges associated with these dynamic and self-configuring networks. Ensuring QoS in MANETs is critical for supporting diverse applications and meeting the specific requirements of different scenarios [3]. The importance of QoS in MANETs can be highlighted in several key aspects:

- **Application Diversity:** MANETs support a wide range of applications, including real-time communication, multimedia streaming, collaborative sensing, and data dissemination. Each application may have distinct QoS requirements, such as low latency for voice and video communication, high reliability for critical data transmission, or efficient energy utilization for resource-constrained devices. QoS mechanisms in MANETs aim to cater to these diverse application needs.

- **Dynamic Topology and Link Variability:** The dynamic and decentralized nature of MANETs leads to frequent changes in network topology and link conditions. QoS mechanisms are essential to adapt routing strategies dynamically, optimizing communication paths based on real-time variations in link quality. This adaptability helps maintain consistent and reliable QoS levels, even in the face of node mobility and changing environmental conditions.
- **Resource Constraints:** MANET nodes are often resource-constrained, with limitations in processing power, memory, and energy. QoS-aware protocols and algorithms take these constraints into account to ensure efficient resource utilization. By optimizing the use of available resources, QoS mechanisms help extend the network's operational lifespan and enhance overall performance.
- **Real-Time Communication Requirements:** Some MANET applications, such as voice and video communication, demand low latency and minimal packet loss to provide a satisfactory user experience. QoS mechanisms address these real-time communication requirements by prioritizing certain types of traffic, ensuring timely delivery, and minimizing delays caused by routing and transmission challenges.
- **Reliability and Packet Delivery:** Reliable packet delivery is crucial in MANETs, especially in mission-critical scenarios such as military operations or disaster response. QoS mechanisms enhance the reliability of data transmission by employing error detection and correction techniques, as well as adaptive routing strategies to mitigate the impact of link failures or congestion.
- **Network Efficiency and Throughput:** QoS considerations contribute to the overall efficiency and throughput of the MANET. By optimizing routing decisions, managing bandwidth effectively, and prioritizing traffic, QoS mechanisms aim to enhance the overall network performance. This is particularly important in scenarios where limited resources must be efficiently utilized.

The importance of Quality of Service in MANETs lies in its ability to tailor communication strategies to meet the specific demands of diverse applications, adapt to the dynamic nature of the network, and ensure reliable and efficient data transmission in resource-constrained environments. QoS-aware routing protocols and mechanisms are essential for the successful deployment and operation of MANETs across various applications and scenarios.

II.RELATED WORKS

Raghu Ramamoorthy et al.,(2022)[4] proposed a Enhanced Bio-Inspired Routing Algorithm (EBIRA) improves communication reliability in Vehicular Ad Hoc Networks (VANETs) by employing enhanced ant colony optimization (EACO). EACO selects optimal routes based on distance, signal strength, hop count, and evaporation rate, resulting in shorter paths with high connectivity and minimized hops. Compared to Reliable Route Discovery with Ant Colony Optimization (RDACO) and Road-Aware Geographic Routing Protocol (RAGR), simulation results demonstrate EBIRA's superior performance in packet delivery ratio, throughput, and latency. Additionally, EBIRA's success is evaluated under varying vehicle density and speed conditions.

Rajiv Yadav et al., (2022) **[5]** this researcher face challenges in developing robust and energy-efficient clustering and routing protocols for Wireless Sensor Networks (WSNs) across various domains. Existing protocols often focus on cluster head election, neglecting other crucial aspects such as cluster formation, data aggregation, and security. While cluster-based routing has addressed some issues, the selection of cluster heads can be further improved by integrating critical characteristics. Nature-inspired algorithms are gaining popularity for addressing challenges like sensor lifespan and transmission distance in WSNs. However, changing sensor node batteries in remote areas is impractical, leading to ongoing research to extend node lifespan. Existing node clustering techniques often suffer from issues like non-uniform cluster head distribution and imbalanced load within clusters. Metaheuristic algorithms (DE, GA, PSO, ACO, SFO, GWO) offer a simple, versatile, and derivation-free approach to optimize energy usage in networks. This paper explores hybridization techniques (DE-GA, GA-PSO, PSO-ACO, PSO-ABC, PSO-GWO) to enhance the energy efficiency of WSNs. The discussion includes speeding up implementation, improving data transfer efficiency, and reducing energy consumption through bio-inspired hybrid optimization algorithms.

Uppalapati Srilakshmi et al.,(2022) **[6]** this research introduced the Bacteria for Aging Optimization Algorithm (BFOA) to enhance trust-based, secure, and energy-efficient navigation in MANETs. The algorithm utilizes a fuzzy clustering approach to select Cluster Heads (CHs) based on trust levels, and optimal multi-hop routing is determined considering latency, throughput, and connection. Compared to existing methods, the proposed BFOA algorithm demonstrates improved energy efficiency, minimal latency, maximum throughput, and an 83% detection rate even without an attack, showcasing its effectiveness in securing MANETs.

Radwa Attia et al.,(2021) [7] this research introduced the Advanced Greedy Hybrid Bio-Inspired (AGHBI) routing protocol, utilizing a greedy forwarding system and a modified hybrid routing scheme with bee colony optimization. The increasing demand for real-time data processing and the growing number of connected vehicles has led to the transformation of VANETs into an automotive Internet of Vehicle (IoV) for a more efficient and intelligent transportation system. The proposed protocol enhances IoV performance by selecting high-quality service routes, maintaining minimum overflow, and demonstrating effectiveness in both Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) environments. Simulation results confirm improved packet delivery ratio, reduced delay, and acceptable overhead and hop count across all vehicles.

Rathore et al.,(2020) [8] researcher introduced a hybrid Whale and Grey Wolf Optimization (WGWO)-based clustering mechanism for Energy Harvesting Wireless Sensor Networks (EH-WSNs). Energy harvesting methods, utilizing sources like solar, wind, mechanical, and temperature variations, can potentially make Wireless Sensor Network (WSN) nodes last indefinitely. To enhance the efficiency and lifetime of energy-constrained sensor nodes, clustering mechanisms are employed. The proposed approach leverages two meta-heuristic algorithms, whale, and grey wolf, resulting in superior exploitation and exploration capabilities compared to traditional metaheuristic algorithms. The hybrid WGWO approach is shown to outperform existing state-of-the-art routing protocols, specifically in terms of cluster formation and dynamically selecting cluster heads (CHs).

III. SYSTEM MODEL

Let V = {1, 2, ..., N} be the set of nodes representing communication devices in the MANET.The set of edges E represents potential communication links between nodes. For an undirected graph, E is an unordered pair of distinct nodes (i, j) , where i, j in V . The adjacency matrix A is a symmetric matrix where A{ij} = 1 if there exists an edge between nodes i and j , and A{ij} = 0 otherwise. The matrix is filled based on the connectivity of nodes, considering communication range and dynamic link conditions. Each link (i, j) is associated with varying conditions: The physical distance between nodes affects signal strength and link quality and representing the signal strength of the wireless communication link. Nodes follow a mobility model, such as the Random Waypoint model, simulating realistic movement patterns. Node positions change over time, impacting the network topology and link conditions. Dynamic Link Formation in Links are dynamically formed and broken based on node proximity and communication range. The network topology evolves over time, reflecting the dynamic nature of MANETs.

Minimize the overall cost function J(x) where x is the routing decision vector for the edges in the graph.

$$J(x)=\sum_{i=1}^{N}\sum_{j=1}^{N}c_{ij}(x_{ij})$$

Quality of Service (QoS) Parameters for each link (i, j), QoS metrics include:

- $P_{ij}(x_{ij})$ - Packet Delivery Ratio on link(i,j)
- $D_{ij}(x_{ij})$ - End-to-End Delay on link (i,j)
- $E_{ij}(x_{ij})$ - Energy Consumption on link (i,j)

The QoS metrics are functions of the routing decisions x_{ij} and network conditions.

IV. OPTIMIZATION ALGORITHMS IN MANET ROUTNIG

Optimization algorithms play a crucial role in Mobile Ad Hoc Networks (MANETs) to address challenges related to routing, resource utilization, and overall network performance. While each algorithm has its strengths, ongoing research focuses on hybrid approaches to capitalize on their complementary features. The review sets the stage for understanding the diverse applications of optimization algorithms in MANETs and their potential contributions to the development of efficient and adaptive networking solutions.

4.1. Ant Colony Optimization (ACO):

The ACO algorithm is a nature-inspired optimization technique based on the foraging behavior of ants. In the context of Mobile Ad Hoc Networks (MANETs), ACO can be applied to QoS-based routing, optimizing paths for metrics such as latency, reliability, or energy efficiency. ACO operates on the principle of decentralized ***decision-making***, where individual agents (ants) collaborate indirectly through the use of stigmergy, a form of communication based on modifying the environment [9][10]. Each ant explores the solution space independently, contributing to the collective intelligence of the system.

- ***Pheromone Communication:*** Ants deposit a chemical substance called pheromone on the paths they traverse. The intensity of the pheromone trail serves as an indirect communication mechanism, indicating the attractiveness of a particular path. Paths with higher pheromone levels are more likely to be chosen by other ants.
- ***Solution Construction:*** Ants build solutions by probabilistically selecting paths based on both pheromone intensity and a heuristic function, which estimates the desirability of a path. Shorter and more optimal paths accumulate higher pheromone levels over time due to the collective choices of ants.
- ***Pheromone Evaporation:*** To prevent the convergence to suboptimal solutions, pheromone levels on all paths gradually evaporate over time. This evaporation process introduces a balance between exploration (searching for new paths) and exploitation (favoring known optimal paths).

ACO Algorithm Workflow:

- ***Initialization:*** Initialize pheromone levels on all paths in the solution space. Set parameters such as the evaporation rate and exploration-exploitation trade-off.

  Pheromone Initialization,

  $\tau_{ij}=\tau_0$ for all edges (i, j), where τ_0 is the initial pheromone value.

  Visibility Initialization,

  $\eta_{ij}=1 / d_{ij}$, where d_{ij} is the distance between nodes i and j.

- ***Ant Movement:*** Deploy a population of artificial ants to construct solutions independently. Ants probabilistically select paths based on pheromone intensity and heuristic information.

  For each ant k, construct a solution by probabilistically selecting the next node based on pheromone intensity and visibility:

  $$p_{ij}^{k}= \tau_{ij}^{\alpha}.\eta_{ij}^{\beta} / \sum(\tau_{ij}^{\alpha}\eta_{ij}^{\beta}) \quad \text{for each edge (i, j).}$$

  Randomly choose the next node j with probability p_{ij}^{k}.

- ***Solution Evaluation:*** Evaluate the quality of each solution constructed by ants based on an objective function.

  Evaluate the constructed solution based on a QoS metric (e.g., latency, reliability):

  Qk=∑QoS metric(i,j) for the path constructed by ant k.

- ***Pheromone Update:*** Adjust pheromone levels on the paths according to the quality of the solutions. Higher-quality solutions contribute more to the pheromone update. Update pheromone levels on all edges based on the quality of solutions,

  $$\tau_{ij}=(1-\rho).\tau_{ij}+\sum_{k}\Delta\tau_{ij}^{k},$$

Where ρ is the evaporation rate and $\Delta\tau_{ij}^{k}$ is the pheromone change made by ant k.

$$\Delta\tau_{ij}^{k}= Q_k / \text{Total QoS of all ants.}$$

- ***Iteration:*** Repeat the process for a predefined number of iterations or until a termination criterion is met.

- ***Pheromone Evaporation:*** Evaporate pheromone on all edges to prevent convergence to suboptimal solutions:

  $$\tau_{ij}=(1-\rho).\tau_{ij},$$

  Where, ρ is the evaporation rate.

  - ***Optimal Path Extraction:*** Extract the optimal path based on the pheromone levels after a specified number of iterations.
  - ***Termination:*** The algorithm terminates based on a predefined stopping criterion (e.g., a maximum number of iterations or convergence to a specific solution quality).

In MANETs, ACO can be applied to solve routing problems by finding optimal paths based on various criteria such as minimizing latency, maximizing throughput, or optimizing energy consumption. The decentralized and adaptive nature of ACO aligns well with the dynamic and self-configuring characteristics of MANETs, making it a suitable choice for addressing routing challenges in these networks.

4.2. Greywolf Optimization Algorithm (GOA)

Greywolf Optimization Algorithm (GOA) is a nature-inspired optimization algorithm inspired by the social hierarchy and hunting behavior of grey wolves [11][12]. Applied to Mobile Ad Hoc Networks (MANETs), GOA can be used for optimization tasks, including QoS-based routing. This section provides an overview of GOA and its potential application in MANETs.

- ***Alpha, Beta, Delta, and Omega Wolves:*** The algorithm simulates the hierarchy in a wolf pack, with four types of wolves representing different roles. Alpha wolf (α) leads the pack, beta wolf (β) supports the alpha, delta wolf (δ) explores and searches for prey, and omega wolf (ω) is a weak and submissive member.
- ***Objective Function:*** GOA aims to optimize an objective function, representing the fitness or cost to be minimized or maximized.
- ***Search Space Exploration:*** Wolves collaborate to explore the search space, adapting their positions based on the fitness of their current solutions.

Algorithm Steps:

- *Initialization:* Initialize the positions of alpha, beta, delta, and omega wolves randomly within the search space.
- *Objective Function Evaluation:* Evaluate the fitness of each wolf's position based on the objective function.
- *Update Positions:* Update the positions of wolves using the following equations:
  - $D_\alpha=|C_1.X_\alpha-X_i|$
  - $D_\beta=|C_2.X_\beta-X_i|$
  - $D_\delta=|C_3.X_\delta-X_i|$
  - $X_\omega=(X_\alpha+X_\beta+X_\delta)/3$
  - $X_i=(X_i+X_\alpha+X_\beta+X_\delta+X_\omega)/5$
- *Boundary Handling:* Ensure that the updated positions remain within the specified boundaries of the search space.
- *Objective Function Re-evaluation:* Re-evaluate the fitness of wolves' new positions.
- *Update Dominant Wolves:* Update the positions of dominant wolves (alpha, beta, delta) based on their fitness values.
- *Termination Criterion:* Repeat the steps until a termination criterion is met (e.g., a maximum number of iterations or convergence).

GOA's adaptability aligns well with the dynamic nature of MANETs, where nodes may move, join, or leave the network unpredictably. The collaborative exploration of the search space by alpha, beta, delta, and omega wolves allows for a balance between exploration of new routes and exploitation of promising ones. The decentralized nature of GOA is suitable for MANETs, as it aligns with the distributed and self-organizing characteristics of these networks. GOA, inspired by the social behavior of grey wolves, offers a promising approach for optimization problems in MANETs, including QoS-based routing. Its adaptability, collaborative exploration, and decentralized nature make it a potential candidate for addressing the dynamic and distributed challenges inherent in MANET environments. Ongoing research and advancements in hybridization with other optimization algorithms may further improve the algorithm's performance and applicability in MANET scenarios.

4.3. Artificial Bee Colony (ABC)

ABC, inspired by the foraging behavior of honeybees, offers a potential solution for QoS-based routing optimization in MANETs [13][14]. Its balance between exploration and exploitation, adaptability, and decentralized nature make it a promising algorithm for addressing the challenges posed by the dynamic and distributed characteristics of MANET environments. This research and advancements in parameter tuning, adaptability to dynamic conditions, and hybridization may further enhance the applicability of the ABC algorithm in MANET routing scenarios.

Employed bees explore the search space and find solutions to the optimization problem. Onlooker bees observe the employed bees and choose a solution based on their performance. Scout bees explore new solutions by generating random positions in the search space.

Steps of the Artificial Bee Colony (ABC) Algorithm,

- *Initialization:* Initialize the population of employed bees with random solutions.
- *Employed Bee Phase:* For each employed bee i, generate a new solution v_i in the neighborhood of the current solution x_i:

  $$v_{ij}=x_{ij}+\phi_{ij}.(x_{ij}-x_{kj})$$

  Where, j is the dimension/index of the solution. k is a randomly chosen employed bee different from i. ϕ_{ij} is a random number in the range [−1,1][−1,1].
- *Fitness Evaluation:* Evaluate the fitness of the newly generated solutions v_i using the objective function: fitness(v_i)
- *Onlooker Bee Phase:* Calculate the probability Pi for each employed bee to be chosen by onlooker bees:

  $$Pi = \text{fitness}(x_i)/ \sum_{i=1}^{n}\text{fitness}(x_i)$$

  Probabilistically choose employed bees based on P_i to become onlooker bees.
- *Fitness Evaluation (Onlooker Bees):* Evaluate the fitness of the solutions chosen by onlooker bees using the objective function.
- *Greedy Selection:* Select the solution with the best fitness (lowest or highest, depending on the optimization type) as the current best solution:

  $$x_{best}=\text{argmin}(\text{fitness}(x_i))$$
- *Scout Bee Phase:* Identify solutions that have not been improved for a specified number of iterations. Replace these solutions with new randomly generated solutions:

$$xij=lower\_bound+rand()\times(upper\_bound-lower\_bound)$$

- *Termination Criterion:* Repeat the process until a termination criterion is met (e.g., a maximum number of iterations or convergence).

Here, n is the total number of employed bees, fitness(x_i) represents the fitness of the solution x_i, and rand() generates a random number between 0 and 1. The algorithm involves exploration by employed and onlooker bees, exploitation by selecting the best solutions, and a mechanism to handle stagnation by scout bees. The fitness function is problem-specific and should be defined based on the optimization task at hand.

V.INTEGRATION OF GREY WOLF OPTIMIZATION (GWO) AND ANT COLONY OPTIMIZATION (ACO):

The integration of Grey Wolf Optimization (GWO) and Ant Colony Optimization (ACO) aims to harness the strengths of both algorithms to create a more robust and efficient optimization approach. GWO provides powerful exploration capabilities, while ACO excels in exploitation and adaptive path construction. The integration involves combining key elements of GWO's wolf pack hierarchy and ACO's pheromone-based communication to achieve a balanced exploration-exploitation trade-off.

In the integration process of GWO, fundamental components include Grey Wolves, where the positions of alpha, beta, and delta wolves serve to represent potential solutions. The Objective Function is employed to assess the fitness of each wolf's position by utilizing the defined objective function. Additionally, the Position Update mechanism from GWO is utilized to efficiently explore the search space. On the other hand, the integration components for ACO comprise Ants, treating them as prospective paths or solutions within the search space. Pheromones are employed to depict the quality of paths constructed by ants. Furthermore, Ant Movement involves allowing ants to probabilistically select paths based on pheromone levels and heuristics, and the Pheromone Update process adjusts pheromone levels based on the quality of solutions (paths) constructed by ants.

Integration Strategies:

- Allow GWO and ACO components to operate concurrently, fostering cooperative exploration and exploitation.
- Facilitate information exchange between GWO and ACO components to guide exploration and exploitation based on the collective knowledge.
- Enable dynamic adaptation of the roles played by alpha, beta, and delta wolves based on the evolving pheromone landscape.

Integrated Algorithm Steps:

1. Initialization: Initialize positions of grey wolves and pheromone levels on paths.
   $$x_{ij} \sim U(a,b) \text{ for all paths}$$
   $$\tau_{ij} = \tau 0 \text{ for all paths}$$
2. GWO Exploration: Utilize GWO's exploration capabilities to update the positions of grey wolves.
   $$x_{ij} = (X_{\alpha,j} + X_{\beta,j} + X_{\delta})/3$$
   $$x_{ij} = \text{BoundaryHandling}(x_{ij})$$
3. ACO Exploitation: Leverage ACO's exploitation capabilities to construct and evaluate paths based on updated positions.
   $$p_{ij} = \tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta} / \sum_{k \in \text{Neighbors}(i)} \tau_{ik}^{\alpha} \cdot \eta_{ik}^{\beta}$$
4. Information Exchange: Exchange information between GWO and ACO components to guide exploration and exploitation dynamically.
5. Update Dominant Wolves and Pheromones: Update positions of dominant wolves based on fitn ess values from GWO.
   $$\tau_{ij} = (1-\rho).\tau_{ij} + \Delta\tau_{ij}$$
6. Where $\Delta\tau_{ij}$ is the pheromone update amount based on ACO’s e valuation.
7. Role Adaptation: Dynamically adapt the roles of alpha, beta, and delta wolves based on the evolving pheromone landscape.
8. Termination Criterion: Repeat the integrated process until a termination criterion is met.

Initialization step, the positions of grey wolves x_{ij} and initial pheromone levels on paths τ_{ij} are set. Grey wolves represent potential solutions, and pheromones represent the attractiveness of paths. GWO's exploration capabilities are employed to update the positions of grey wolves. The new positions are calculated by averaging the positions of alpha, beta, and delta wolves in each dimension. Boundary handling ensures that the updated positions remain within the defined search space. ACO's exploitation capabilities are utilized to construct and evaluate paths based on the updated positions of grey wolves. Ants probabilistically select paths based on the pheromone levels and heuristic information, aiming to exploit promising regions in the search space. Information exchange occurs between the GWO and ACO components to dynamically guide exploration and exploitation. The specifics of information sharing depend on the problem at hand and may involve updating algorithm parameters or sharing insights gained during the exploration and exploitation phases.

The positions of dominant wolves (alpha, beta, and delta) are updated based on fitness values obtained from GWO's exploration. Additionally, pheromone levels are updated based on the quality of paths constructed by ACO. Pheromone evaporation is considered to prevent stagnation. The roles of alpha, beta, and delta wolves are dynamically adapted based on the evolving pheromone landscape and GWO's performance. This adaptation ensures that dominant wolves effectively guide the exploration and exploitation phases of the integrated algorithm. The integrated process is repeated until a termination criterion is met. This criterion could be a maximum number of iterations, convergence to a satisfactory solution, or other problem-specific conditions. The repetition of steps allows the algorithm to iteratively refine solutions. In summary, the integrated algorithm combines the exploration strengths of GWO with the exploitation capabilities of ACO. It establishes a dynamic interaction between the two components, allowing them to share information and adapt to the evolving problem landscape. The integration aims to achieve a balanced exploration-exploitation trade-off, leading to improved convergence and robustness in solving optimization problems.

V. EXPERIMENTAL RESULT

All simulations are executed on NS3 simulations on Microsoft Windows 7 machine with configuration CORE i5, 4 GB RAM and 2.2 GHz processor. Table 1 characterizes the simulation parameters as shown. The results of PSO and GA Algorithms are compared using the QoS parameters, including data End-to-end delay, Packet Delivery Ratio and Routing overhead by respect to the number of nodes. Initially, each node in MANET is considered with the trust value of 0.5. The simulation has been carried with different node densities as of 50, 100, 150 and 250 nodes. Here, the total number of mobile nodes in the network is considered to be the population of trusted model. The numbers of malicious nodes tested are 12 up to 20 in multiples of 2 increasing by 2 for 10 different topologies.

Table 1: Simulation Parameter

Parameter	Values
No. of Nodes	250
Area Size	1000 X 1000 m
Mac	802.11
Radio Range	250m
Simulation Time	120 sec
Traffic Source	CBR
Packet Size	150 bytes

Performance Metric: Performance metrics play an important role in evaluating the effectiveness of Quality of Service (QoS)-based routing algorithms in Mobile Ad Hoc Networks (MANETs) [15][16]. The evaluation metrics are end to end delay, packet delivery ratio and energy consumption. In the context of Artificial Bee Colony(ABC), Ant Colony Optimization(ACO), and Greywolf Optimization(GWO) and Hybrid Greywolf Optimization and Ant Colony(GW-ACO) Optimization Algorithms.

End-to-End Delay: End-to-End Delay represents the total time taken for a packet to traverse the network from source to destination, encompassing transmission, propagation, queuing, and processing delays. Figure 1 shows the comparative scenario for ACO, ABC, GWO and Hybrid GW-ACO based algorithms towards End to End Vs Number of nodes. In this assessment, the Hybrid GW-ACO algorithm is identified as the best-performing solution, excelling in minimizing End-to-End Delay. This hybrid approach leverages the strengths of both GWO and ACO, achieving a balanced exploration-exploitation trade-off and adaptability to dynamic network conditions. The comparison involves metrics such as average End-to-End Delay and standard deviation, emphasizing the hybrid algorithm's superior efficiency in optimizing packet delivery within the desired timeframe, making it a promising choice for routing in MANETs. The hybrid approach can adapt routing paths to minimize delay based on the network's evolving conditions.

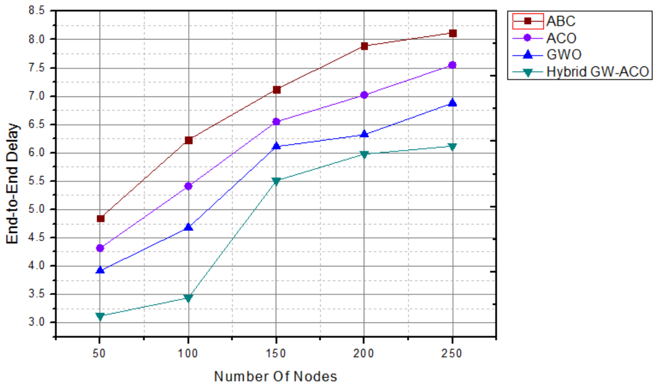

Figure 1: End to End Delay

Energy consumption: The assessment of routing algorithms, comprising ACO, ABC, GWO and Hybrid GW-ACO, focuses on the critical performance metric of Energy Consumption in Mobile Ad Hoc Networks (MANETs).

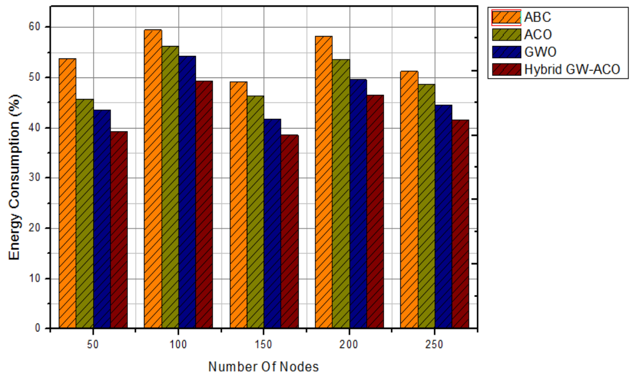

Figure 2: Energy Consumption

Energy Consumption measures the amount of energy utilized by nodes during data packet transmission and routing. In this evaluation, the Hybrid GW-ACO emerges as the top-performing algorithm, showcasing superior results in minimizing Energy Consumption. Figure 2 shows; this hybrid solution strategically combines the exploration capabilities of GWO with the adaptive routing features of ACO, achieving an optimal balance between energy-efficient paths and adaptability to dynamic network conditions. The comparison involves metrics such as average energy consumption and standard deviation, highlighting the Hybrid GW-ACO's efficiency in conserving energy resources, making it a promising choice for energy-aware routing in MANETs.

Packet Delivery Ratio (PDR): The evaluation of routing algorithms, encompassing ACO, ABC, GWO and Hybrid GW-ACO, centers on the crucial performance metric of Packet Delivery Ratio in Mobile Ad Hoc Networks (MANETs). Packet Delivery Ratio measures the proportion of successfully delivered packets to their intended destinations, reflecting the algorithm's efficiency in ensuring reliable data transmission. Figure 3 shows, this assessment; the Hybrid GW-ACO emerges as the superior performer, demonstrating the highest Packet Delivery Ratio. This hybrid approach strategically integrates the exploration capabilities of GWO with the routing efficiency of ACO, achieving a robust balance between packet delivery success and adaptability to dynamic network conditions. The comparison involves metrics such as average Packet Delivery Ratio and standard deviation, underscoring the Hybrid GW-ACO's effectiveness in optimizing reliable packet delivery, making it a promising choice for enhancing communication reliability in MANETs.

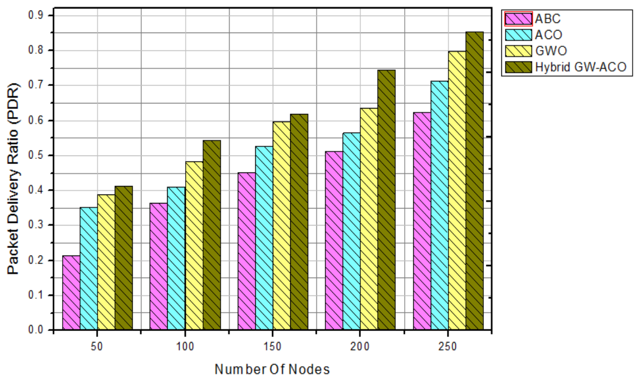

Figure 3: Packet Delivery Ratio (PDR)

VI.CONCLUSION

In conclusion, the evaluation of routing algorithms in Mobile Ad Hoc Networks (MANETs) based on key performance metrics such as End-to-End Delay, Energy Consumption, and Packet Delivery Ratio reveals the Hybrid GW-ACO as the optimal solution among Ant Colony

Optimization (ACO), Artificial Bee Colony (ABC), and Grey Wolf Optimization (GWO). The Hybrid GW-ACO, integrating the strengths of GWO and ACO, demonstrates superior performance across these metrics. In terms of End-to-End Delay, the hybrid algorithm efficiently balances exploration and exploitation, leading to timely and reliable data packet delivery. Additionally, in the context of Energy Consumption, the Hybrid GW-ACO excels in conserving energy resources while ensuring effective routing. Moreover, the Packet Delivery Ratio metric highlights the hybrid algorithm's ability to achieve a high success rate in delivering packets to their intended destinations. This comprehensive evaluation underscores the Hybrid GW-ACO as a promising and versatile solution for optimizing routing in MANETs, offering improved efficiency, energy conservation, and reliable packet delivery in dynamic network environments. Further research and experimentation are warranted to validate the robustness and scalability of the proposed hybrid algorithm across diverse MANET scenarios.

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