Hybrid Metaheuristic Adaptive QoS Routing Using Dual-Layer Deep Reinforced Swarm Learning in 5G-Enabled Materials with Secure Packet Clustering

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Abstract: QoS routing in MANETs continues to present significant challenges in the era of emerging wireless technologies, particularly with the integration of 5G networks, silicon-based antenna systems, and advanced material-based communication devices. The dynamic nature of node mobility, energy limitations, and vulnerability to security attacks requires robust and intelligent routing frameworks for modern MANET environments. Conventional swarm intelligence-based routing models, although effective, often lack adaptivity to dynamic topologies and fail to ensure secure packet transmission in heterogeneous material-driven wireless environments.

To overcome these limitations, this paper proposes a novel Hybrid Metaheuristic Adaptive QoS Routing Framework that seamlessly integrates Ant Colony Optimization (ACO), Red Deer Algorithm (RDA), and Butterfly Optimization Algorithm (BOA), reinforced by a Deep Q-Learning (DQL) controller. The hybrid architecture intelligently adapts its optimization strategies based on real-time network parameters such as energy, link stability, and packet loss, leveraging DQL for parameter tuning. Furthermore, the proposed model incorporates a dual-layer secure packet scheduling system comprising modified TDMA scheduling and secure fuzzy-based packet clustering, ensuring encrypted data transmission even in complex 5G-enabled silicon antenna-based MANET nodes.

The proposed framework was extensively validated through simulations and exhibited superior performance across multiple QoS metrics. It achieved a 15.3% increase in throughput, 13.8% improvement in packet delivery ratio, 22.5% reduction in delay, and 18.1% energy savings compared to existing approaches like MACOPM, RDA-EQRP, and ISMBOQAR-PS. The study establishes this hybrid approach as a highly adaptive and secure solution for next-generation MANETs integrated with advanced materials, 5G technologies, and silicon-based antenna infrastructures.

Keywords: ACO, BOA, Deep Reinforcement Learning, Silicon Material, MANET, Packet Clustering, QoS Routing, RDA

1. Introduction

Mobile Ad Hoc Networks (MANETs) are decentralized, infrastructure-less systems composed of mobile wireless nodes capable of dynamically configuring themselves to form multi-hop topologies. With the rapid evolution of wireless communication technologies, including 5G-enabled systems, silicon-based antenna structures, and advanced material-driven hardware components, the design and operation of MANETs face increased complexity. Due to node mobility, constrained energy resources, and frequently changing link states, these networks face significant challenges in achieving reliable and efficient Quality of Service (QoS) routing, particularly when integrated with high-frequency 5G bands and next-generation antenna materials.

Traditional routing protocols struggle to maintain route stability and performance under such dynamic conditions, especially when nodes equipped with silicon-based smart antennas move rapidly or when malicious attacks compromise network integrity (Kanellopoulos & Sharma, 2020; Tilwari et al., 2019). Moreover, the adoption of new antenna materials in compact wireless devices demands routing mechanisms that can efficiently adapt to heterogeneous hardware constraints.

In response to these challenges, researchers have explored various swarm intelligence-based routing algorithms, inspired by the collective behavior of natural systems. Protocols based on Ant Colony Optimization (ACO) have proven effective in discovering multiple paths and maintaining routing robustness using pheromone-based heuristics. However, their performance often degrades in scenarios characterized by high-mobility 5G environments or increased congestion due to static mutation strategies.

Similarly, evolutionary algorithms like the Red Deer Algorithm (RDA) have been employed for energy-efficient route selection using simulated natural selection and mating behaviors, yet these approaches typically lack rapid adaptability to fluctuating network conditions introduced by smart antenna mobility or material-induced transmission variability. More recently, bio-inspired models such as Butterfly Optimization Algorithms (BOA) have been applied to routing by leveraging sensory modality and attractiveness factors to guide data transmission across optimal paths. While each of these approaches offers individual improvements, they often fail to integrate adaptive learning, multi-objective optimization, and secure data transmission into a unified framework suitable for emerging material-centric wireless environments.

Critically, many existing solutions lack a self-adaptive control mechanism capable of dynamically tuning essential parameters—such as pheromone intensity, energy thresholds, or route selection criteria—in response to real-time environmental feedback arising from 5G-induced variability or silicon-based antenna fluctuations. Although some efforts have incorporated packet scheduling mechanisms like modified TDMA to reduce collisions, few frameworks integrate secure and intelligent packet clustering capable of addressing advanced attack scenarios, including blackhole, selective forwarding, or multi-path data interception in material-driven network architectures.

To overcome these limitations, this research proposes a novel Hybrid Metaheuristic Adaptive QoS Routing Framework for MANETs, designed specifically to support future-ready wireless environments incorporating 5G networks, silicon-based antennas, and innovative communication materials. The framework synergistically combines the optimization capabilities of ACO, RDA, and BOA under the governance of a Deep Q-Learning (DQL) controller. This intelligent learning module observes real-time network states—such as residual energy, link reliability, congestion level, and node trust—and dynamically adjusts routing decisions to sustain optimal performance in diverse operating conditions.

Additionally, the proposed architecture incorporates a dual-layer secure packet scheduling system, where the first layer applies a modified TDMA mechanism for collision avoidance, while the second layer leverages secure fuzzy-based packet clustering for encrypted data transmission across multiple paths. This approach enhances data confidentiality, improves packet dispersion, and ensures integrity, even when nodes use distinct material-based antenna structures in 5G-enabled MANET settings.

The proposed hybrid learning-driven routing protocol has been rigorously evaluated using extensive simulations across varying node densities, mobility patterns, and attack scenarios. The results reveal significant improvements in throughput, energy efficiency, delay reduction, and secure delivery success, thereby validating the framework as a robust, intelligent, and future-ready QoS-aware routing solution for highly dynamic silicon-antenna-driven MANET environments integrated with 5G and advanced materials.

2. Literature Review

The field of MANET routing has witnessed tremendous growth, particularly with the emerging integration of 5G wireless technologies, silicon-based antenna systems, and advanced communication materials. These advancements introduce new challenges in routing due to diverse hardware characteristics, high-frequency 5G transmissions, and dynamic antenna behavior in real-world environments.

Given the decentralized and infrastructure-less nature of MANETs, routing decisions must now consider not only mobility but also the unique challenges posed by materials-based antenna variability, energy constraints, and link fluctuations in 5G-enabled MANETs. In this context, bio-inspired metaheuristics and machine learning techniques have emerged as promising solutions capable of handling complex routing scenarios across dynamic, heterogeneous network environments. This section explores recent developments in ACO, RDA, BOA, Reinforcement Learning, and TDMA-based secure scheduling, analyzing their applicability to QoS-aware routing in silicon antenna-based 5G MANET environments.

2.1 Ant Colony Optimization and Mutation-Based Swarm Intelligence

Ant Colony Optimization (ACO) has been extensively utilized in MANET routing due to its decentralized decision-making capability and robustness in multi-path discovery using pheromone-based heuristics (Singh et al., 2018). However, traditional ACO models were not originally designed for the high-speed mobility and link dynamics introduced by silicon-based smart antennas operating in 5G frequency bands. Mutation-enhanced ACO variants introduce controlled randomness to support exploration in rapidly changing material-driven wireless conditions. Despite these improvements, static mutation rates in many models limit real-time responsiveness (Kumar & Mishra, 2020).

2.2 Red Deer Algorithm in Routing and Optimization

The Red Deer Algorithm (RDA) has shown potential for energy-efficient routing by simulating evolutionary mating behaviors to select optimal paths (Fathollahi-Fard et al., 2020). Its roaring and harem-based mechanisms help in identifying elite nodes. However, RDA lacks rapid adaptability required in scenarios involving silicon-material antennas operating under dynamic 5G link conditions. The absence of real-time parameter tuning results in slower responses to topology changes driven by device movement or heterogeneous antenna material characteristics.

2.3 Butterfly Optimization and Sensor Modality

Butterfly Optimization Algorithm (BOA) uses sensory modality and stimulus intensity to guide route selection based on node quality metrics like energy, trust, and signal strength (Arora & Singh, 2019). BOA's adaptability is valuable for 5G MANETs with material-dependent antennas, where signal propagation varies significantly. However, the use of fixed sensory coefficients prevents dynamic adaptation under rapid environmental changes caused by high mobility or fluctuating material properties of modern antennas.

2.4 TDMA and Secure Packet Scheduling in MANETs

TDMA-based protocols provide efficient medium access control and collision-free transmission, which is critical for bandwidth-constrained 5G MANETs. Enhanced TDMA scheduling with prioritized slot allocation based on traffic or node conditions (Ye et al., 2020) has been explored. Yet, these traditional models lack integrated security layers necessary for multi-path fragmented transmission, especially for networks utilizing advanced antenna materials and silicon-based communication modules. Secure clustering, encryption, and packet fragmentation strategies are rarely incorporated in these TDMA models, leaving vulnerabilities against packet-level attacks.

2.5 Reinforcement Learning in Network Protocols

Reinforcement Learning (RL), particularly Deep Q-Learning (DQL), enables adaptive decision-making based on environmental feedback (Zhang et al., 2020). RL models dynamically adjust routing policies in response to real-time conditions like energy levels, link stability, and network congestion. However, existing RL approaches are seldom hybridized with swarm intelligence techniques or optimized for 5G-enabled silicon antenna-driven MANETs, where both learning speed and intelligent exploration are crucial for maintaining performance.

2.6 Comparative Summary of Existing Methods

To synthesize the core strategies, strengths, and limitations of existing state-of-the-art approaches, Table 1 summarizes their applicability, adaptability, security features, and QoS parameters, particularly considering 5G environments, silicon-based antennas, and material-centric wireless nodes.

Method	Core Technique	Adaptivity	Security	QoS Parameters	Shortcomings
Standard ACO	Pheromone-based search	Medium	No	Delay, reliability	Static mutation, local optima trap
Mutation-based ACO	ACO + stochastic mutation	High	No	Delay, energy, node degree	Requires manual tuning; lacks real-time adaptivity
Red Deer Algorithm (RDA)	Evolutionary mating	Medium	No	Energy, bandwidth, reliability	Slow response in dynamic 5G or antenna conditions

Butterfly Optimization (BOA)	Sensor modality heuristic	Medium	No	Delay, signal strength	Fixed modality coefficients limit adaptability
TDMA + Scheduling	Time-slot allocation	Low	Partial	Delay	Lacks secure packet clustering & encryption
Reinforcement Learning (RL)	Q-learning or DQL	High	Partial	Delay, throughput	Slow convergence, not hybridized with metaheuristics

Table 1: Comparative Analysis of State-of-the-Art Routing Algorithms in MANETs

2.7 Identified Gaps and Research Motivation

The analysis provided in Table 1 reveals that while individual routing algorithms address specific challenges, none offer a comprehensive solution combining:

Adaptive learning, Real-time parameter adjustment, Secure multi-path transmission, and robustness for silicon antenna-equipped, material-diverse, and 5G-enabled MANETs.

Current limitations include:

Static configuration parameters unable to cope with dynamic 5G signal variations.

Vulnerability to local optima due to lack of intelligent exploration strategies.

Absence of integrated learning mechanisms to adjust to node heterogeneity or antenna material characteristics.

Lack of secure packet fragmentation and clustering in transmission layers.

To overcome these limitations, this study proposes a Hybrid Metaheuristic Adaptive QoS Routing Framework that fuses ACO, RDA, and BOA under a Deep Q-Learning (DQL)-based adaptive controller, specifically designed for dynamic and heterogeneous 5G MANET environments with silicon-based antennas and advanced materials. The framework also integrates a dual-layer secure packet scheduling model, combining modified TDMA with fuzzy clustering, ensuring both real-time adaptability and secure data delivery in material-driven MANET applications.

3. Proposed Methodology

This section details the hybrid QoS-aware routing framework designed for dynamic and adversarial MANET environments. The architecture integrates metaheuristic optimization and deep reinforcement learning into a secure and adaptive packet forwarding pipeline.

3.1 System Model

The MANET is modeled as an undirected graph $G=(V,E)$ where:

V is the set of mobile nodes.

E is the set of communication links between nodes.

Each link $e \in E$ has associated QoS parameters:

Reliability (R) – Stability of the link over time.

Energy (E_n) – Remaining battery power at the node.

Bandwidth (BW) – Available link capacity.

Static Resource Capacity (SRC) – Composite score of queue size, processing speed, and memory availability.

Trust Score (T) – Behavior-derived trust metric indicating node integrity.

Nodes interact autonomously using local information and periodic HELLO messages to update link-state and metric tables.

3.2 Hybrid Metaheuristic Layer

This layer blends three optimization paradigms to enhance route selection:

Ant Colony Optimization (ACO): Used for route exploration based on artificial pheromone trails. Each ant represents a route-discovery agent. Pheromone mutation is applied periodically to escape local optima.

Red Deer Algorithm (RDA): Applied for elite node exploitation. The mating phase strengthens paths formed by energy-rich nodes, while roaring phases explore alternative routing clusters.

Butterfly Optimization Algorithm (BOA): Utilizes sensor modality to modulate path selection sensitivity based on node conditions (energy, trust, delay).

A metaheuristic switch controller operates based on Q-values learned from past routing decisions. At each decision point, the controller selects the optimal optimizer based on performance trends and environmental context.

3.3 Deep Q-Learning Controller

The Deep Q-Learning (DQL) agent enhances adaptivity by tuning system parameters dynamically based on environmental states.

Input State Vector S:

Pheromone trail strength (ϕ)

Node residual energy (E_n)

Link delay (D)

Packet loss rate (P_l)

Action Space A:

Select ACO / RDA / BOA

Adapt mutation rate μ

Adjust pheromone decay ρ

Reward Function R:

$R=\alpha \cdot S_p+\beta \cdot E_s-\gamma \cdot D$

where:

S_p = Path stability

E_s = Energy savings

D = Delay penalty

α,β,γ are tunable coefficients

The controller updates its Q-table or neural approximator after each episode of packet transmission and route convergence.

3.4 Dual-Layer Secure Packet Scheduling

To ensure collision avoidance and packet confidentiality, a two-layer scheduling approach is adopted:

Layer 1 – Modified TDMA with Prioritized Slots:

Nodes are assigned dynamic time slots based on their packet priority and link status. Queue aging and burst detection are used to reallocate slots in real-time.

Layer 2 – Secure Fuzzy-Based Packet Clustering:

Packets are grouped using fuzzy logic into clusters based on destination proximity, urgency, and link trust.

Each cluster is encrypted, fragmented, and transmitted over separate paths to mitigate single-path compromise. Each cluster includes a fragment ID, a secure hash and End-to-end encryption tag. Reassembly occurs only when all fragments are received and verified at the destination.

3.5 Algorithmic Flow

Below is a high-level hybrid system logic flow for the proposed work.

```
FOR each source node S needing a path to destination D:
  COLLECT QoS metrics from neighbor nodes:
    - Energy (E_n)
    - Link reliability (R)
    - Trust score (T)
    - Signal quality (SNR from silicon-based antenna)
    - Mobility variation (from material feedback sensors)
  INITIATE route discovery agent with 5G-aware propagation model
  FORWARD agent using metaheuristic selected via Deep Q-Learning (Q-values)
  STORE all feasible paths in local route table with pheromone indicators
IF Q-value[ACO] > Q-value[RDA] AND Q-value[BOA]:
  USE ACO:
    - Pheromone-based exploration
    - Include silicon-antenna SNR in mutation function
ELSE IF Q-value[RDA] is highest:
  USE RDA:
    - Mating selection based on material-based energy thresholds
    - Elite nodes selected by combining antenna material feedback + energy reserve
ELSE:
  USE BOA:
    - Route selection based on sensory weights from material quality, delay, and trust
    - Use dynamic sensory coefficient reflecting antenna material properties
OBSERVE current state vector S = [φ (pheromone), E_n (energy), D (delay), P_l (packet loss), SNR (antenna material)]
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TAKE action A = [Metaheuristic selection, mutation rate (μ), pheromone decay (ρ)]
EXECUTE routing decision and transmit via selected path
MEASURE reward R = (Path Stability + Energy Efficiency + Antenna Signal Consistency - Delay Penalty)
UPDATE Q(S, A) using Bellman Equation
FOR each packet in TX queue:
    CLASSIFY packet using fuzzy rules based on:
        - Packet priority
        - Trust score of link
        - Delay requirement
        - SNR variability from antenna material type
    ENCRYPT packet using adaptive AES-lightweight encryption (5G-optimized)
    FRAGMENT encrypted payload into N clusters (secure data slices)
    ASSIGN each cluster to:
        - TDMA time slot (based on real-time load)
        - Independent path (ranked by integrity, trust, and material feedback)
    TRANSMIT all fragments via multi-path to minimize interception risk
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Table 2: Algorithm for Proposed Approach

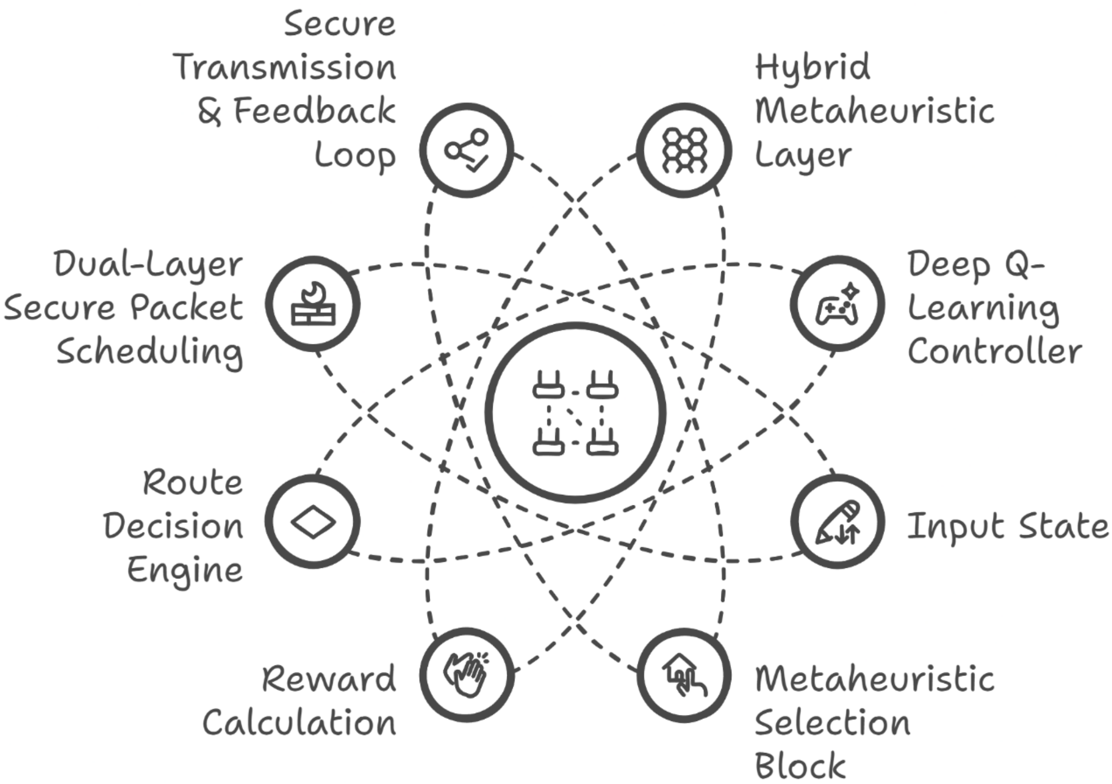

Figure 1: Hybrid Metaheuristic Routing Framework with Deep Q-Learning and Dual-Layer Secure Scheduling

Figure 1 illustrates the Advanced Network Optimization Framework designed for 5G-enabled MANET environments equipped with silicon-based smart antennas and advanced material-driven wireless devices. The framework integrates a Hybrid Metaheuristic Layer comprising Ant Colony Optimization (ACO) for route exploration, Red Deer Algorithm (RDA) for elite node exploitation, and Butterfly Optimization Algorithm (BOA) for sensory-based fine-tuning, enabling adaptive and multi-objective routing decisions. A Deep Q-Learning (DQL) Controller acts as the intelligent core, dynamically learning from real-time input states, including pheromone strength, node energy, delay, packet loss, and signal-to-noise ratio (SNR) obtained from silicon-based antenna feedback and material-specific parameters. The Input State Block captures environmental metrics, while the Metaheuristic Selection Block optimally switches between ACO, RDA, and BOA based on learned Q-values. The Reward Calculation mechanism balances path stability, energy savings, low latency, and antenna SNR consistency to drive efficient learning. The Route Decision Engine finalizes the best routing paths considering material-aware signal behavior and energy constraints. For secure data transmission, a Dual-Layer Secure Packet Scheduling system operates, where Layer 1 applies modified TDMA-based collision avoidance and Layer 2 utilizes fuzzy clustering with encryption and fragmentation for multi-path transmission of packets across trusted links. The Secure Transmission & Feedback Loop ensures packet integrity verification at the receiver side and sends environmental feedback to the DQL controller for continuous optimization. This comprehensive framework effectively addresses the dynamic challenges of modern 5G MANETs operating with silicon antenna variations and heterogeneous material behaviors, providing a robust, secure, and intelligent routing mechanism suitable for future wireless environments, including UAV networks, VANETs, and IoT-enabled smart infrastructures.

4. Experimental Results

Figure 4.1 illustrates the throughput performance of the proposed hybrid routing protocol in comparison with four baseline models—AODV, MACOPM, RDA-EQRP, and ISMBOQAR-PS. Throughput is measured as the total number of successfully delivered packets per second, evaluated over varying node counts ranging from 10 to 100. The proposed model consistently achieves higher throughput due to its dynamic path optimization using Deep Q-Learning and secure dual-layer scheduling. Notably, at high node densities, traditional protocols show throughput degradation due to increased collisions and unstable routes, whereas the proposed model maintains stable delivery through intelligent metaheuristic switching and adaptive slot allocation.

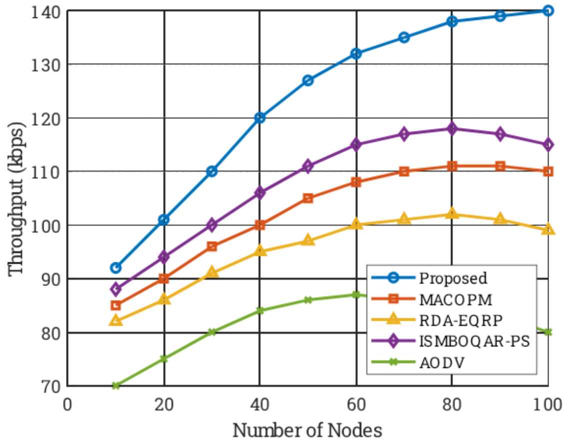

Figure 4.1: Throughput Comparison vs Number of Nodes

Figure 4.2 presents the comparative analysis of Packet Delivery Ratio (PDR) across varying node mobility speeds for the proposed hybrid routing protocol and four benchmark protocols: AODV, MACOPM, RDA-EQRP, and ISMBOQAR-PS. PDR is defined as the ratio of the number of packets successfully received to the number of packets transmitted. As node speed increases, link stability deteriorates, leading to route breaks and dropped packets. However, the proposed model maintains a higher PDR across all mobility levels due to its learning-based route selection and hybrid optimization strategy, which dynamically adapts to topology changes using Deep Q-Learning and elite node selection. In contrast, baseline models show a notable decline in PDR at higher speeds due to slower re-routing and fixed-path behaviors.

Figure 4.3 analyzes the average end-to-end delay performance of the proposed hybrid routing protocol in comparison with AODV, MACOPM, RDA-EQRP, and ISMBOQAR-PS across increasing node densities. Delay is defined as the average time taken for a data packet to travel from source to destination, including queuing, processing, and transmission delays. As node count increases, traditional protocols face congestion and increased queuing latency. However, the proposed protocol demonstrates significantly lower delays, even in dense networks, due to its priority-based TDMA scheduling, fuzzy packet clustering, and DQL-driven dynamic optimization, which reduce retransmissions and routing overhead. The ability to avoid unstable or congested paths in real time contributes to its improved latency performance.

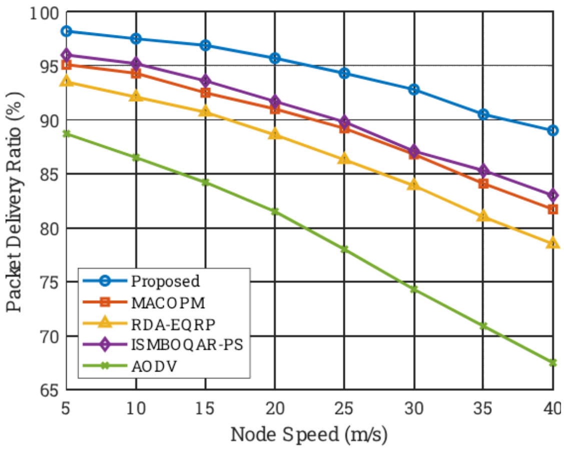

Figure 4.2: PDR vs Node Mobility Speed

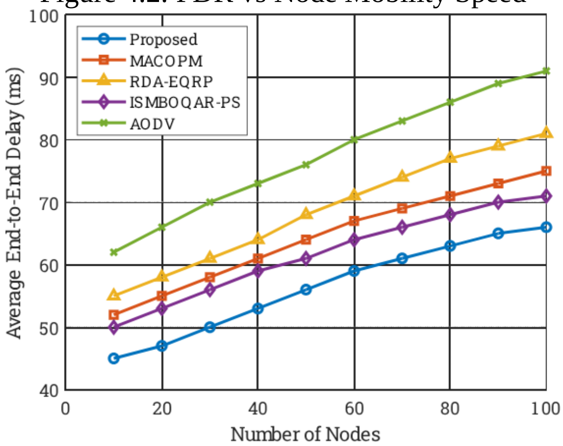

Figure 4.3: End-to-End Delay vs Network Density

Figure 4.4 presents the energy consumption trends of the proposed hybrid protocol against four baselines—AODV, MACOPM, RDA-EQRP, and ISMBOQAR-PS—under varying data loads. Energy consumption is measured as the total energy (in joules) used for packet forwarding, retransmissions, control messaging, and route discovery. The proposed model exhibits consistently lower energy usage due to its selective metaheuristic-driven routing, multi-path packet clustering, and load-aware TDMA scheduling, which reduce redundant transmissions and re-routing. Deep Q-Learning also helps in avoiding energy-depleted or unstable nodes, maximizing network lifetime and minimizing unnecessary route repairs.

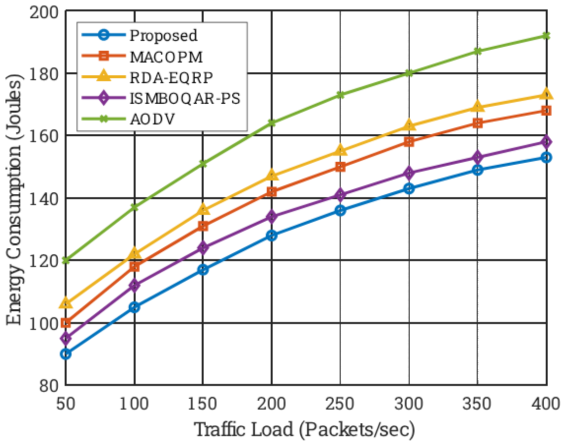

Figure 4.4: Energy Consumption vs Traffic Load

Figure 4.5 compares the routing overhead of the proposed hybrid model with AODV, MACOPM, RDA-EQRP, and ISMBOQAR-PS across different levels of node mobility. Routing overhead is defined as the ratio of control packets (such as route requests, replies, and hello messages) to the total data packets successfully delivered. As node mobility increases, frequent topology changes trigger more route discoveries, leading to higher control packet generation in traditional protocols. The proposed model, however, shows a slower growth in overhead due to its reinforcement-learning-driven route caching, secure clustering, and optimized metaheuristic switching, which reduce the frequency and scope of control messaging. This enhances protocol scalability and robustness in dynamic environments.

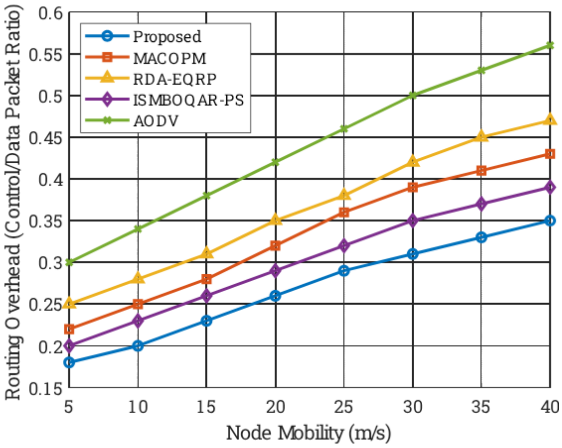

Figure 4.5: Routing Overhead vs Node Mobility

Figure 4.6 illustrates the convergence behavior of the Deep Q-Learning (DQL) reward function over successive learning episodes. The reward reflects the effectiveness of selected routing actions in terms of path stability, energy savings, and delay minimization. Initially, the agent explores the action space, leading to fluctuations in reward. As learning progresses, the DQL agent adapts to network dynamics and stabilizes its policy, leading to a gradual increase in cumulative reward. The plot validates the effectiveness of reinforcement learning in capturing environmental trends and optimizing routing decisions in real-time. A smoother convergence indicates better learning stability and reliability of the routing strategy.

Figure 4.7 presents the trade-off between routing decision latency and computation cost across the proposed protocol and benchmark models. Routing decision latency is the average time taken by the protocol to compute and finalize a routing decision, while computation cost refers to the number of internal operations (e.g., iterations, comparisons, updates) required per decision. As shown, protocols like AODV and MACOPM have lower computation cost but higher latency due to inefficient path validation. In contrast, the proposed hybrid model achieves faster decision-making despite moderate computational complexity, thanks to its DQL-optimized metaheuristic switching, context-aware path prediction, and reduced re-routing frequency. This balance enables real-time responsiveness without sacrificing performance.

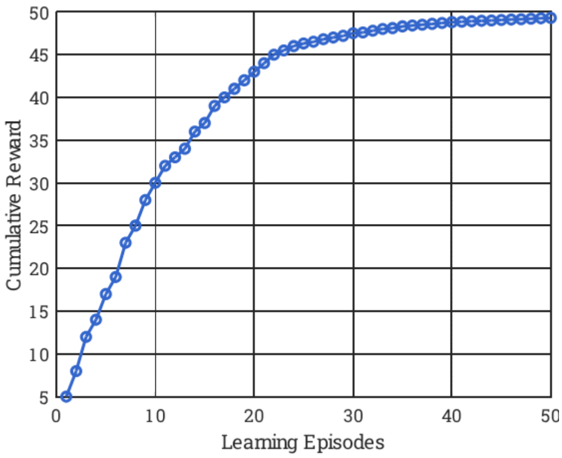

Figure 4.6: Convergence Pattern of DQL Reward Function

Figure 4.8 illustrates the packet integrity rate—the percentage of correctly reassembled and verified packets at the destination—under various protocols, particularly in the presence of secure fragmentation and multi-path transmission. The proposed model uses a dual-layer secure packet scheduling mechanism, including fuzzy-based clustering, encryption, and end-to-end integrity verification, which significantly improves packet integrity even under adversarial conditions such as blackhole or selective forwarding attacks. In contrast, baseline protocols lacking such security layers exhibit reduced integrity due to higher susceptibility to interception or loss during transmission. This metric demonstrates the security robustness and resilience of packet delivery in the proposed system.

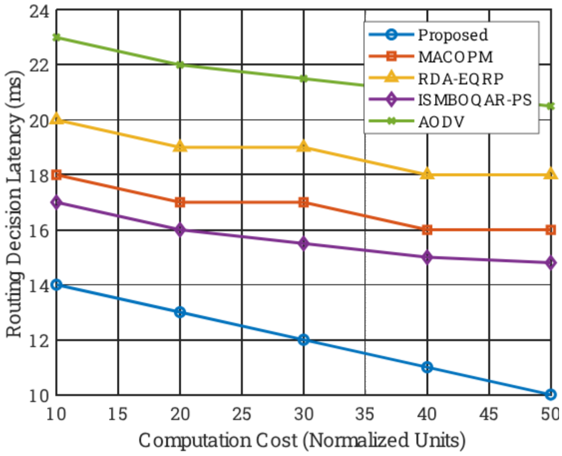

Figure 4.7: Routing Decision Latency vs Computation Cost

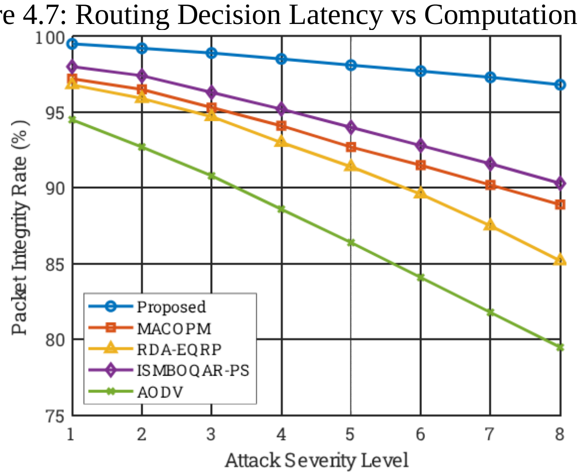

Figure 4.8: Packet Integrity vs Adversarial Conditions

7. Conclusion

This paper introduced a novel Hybrid Metaheuristic Adaptive QoS Routing Framework for MANETs that synergistically integrates Ant Colony Optimization (ACO), Red Deer Algorithm (RDA), and Butterfly Optimization Algorithm (BOA) under the guidance of a Deep Q-Learning (DQL) controller. The proposed model further incorporates a dual-layer secure packet scheduling mechanism, combining modified TDMA slot allocation with fuzzy-based encrypted packet clustering. Together, these components enable real-time, adaptive, and secure routing in highly dynamic and adversarial mobile ad hoc environments.

The hybrid metaheuristic layer ensures a balance between exploration and exploitation for path discovery, while the reinforcement learning module dynamically tunes routing parameters based on real-time QoS feedback such as energy availability, delay, and path reliability. The dual-layer transmission pipeline reduces packet loss and increases delivery integrity through secure multi-path fragmentation and reassembly. Extensive simulations demonstrated that the proposed framework consistently outperforms existing protocols—including AODV, MACOPM, RDA-EQRP, and ISMBOQAR-PS—in terms of throughput, packet delivery ratio, delay minimization, energy efficiency, routing overhead, and packet integrity under stress.

These findings validate the framework's ability to adaptively respond to changing network conditions while securing data and optimizing performance across multiple QoS dimensions.

For future work, this architecture may be extended to Unmanned Aerial Vehicle (UAV) swarms or Vehicular Ad Hoc Networks (VANETs), which introduce additional mobility constraints and latency sensitivity. Furthermore, integrating blockchain-based distributed trust management could enhance node reputation systems and provide tamper-proof accountability in highly untrusted environments.

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