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AI-HTP- Hybrid Transport Routing Protocol for Cognitive Radio Ad-Hoc Networks: A Novel Model with Cross-Layer Network Parameter Optimization using AI Learning

Majid Shaikh
Research Scholar, Sai Vidya Institute of technology, Bengaluru
Dr. Priti Mishra
Professor, Sai Vidya Institute of technology, Bengaluru

Abstract

Cognitive Radio Networks (CRNs) have evolved as a transformative paradigm for improving spectrum efficiency by opportunistically exploiting underutilized or idle licensed frequency bands within dynamic radio environments. The fundamental principle of CRNs is to enable Secondary Users (SUs) to opportunistically access the licensed spectrum, provided that their transmissions do not cause harmful interference to Primary Users (PUs). However, due to the stochastic and time-varying activity of PUs, channel availability becomes highly uncertain, leading to frequent disruptions and intermittent connectivity. This problem becomes even more pronounced in Cognitive Radio Ad-Hoc Networks (CRAHNs), where the absence of fixed infrastructure, multi-hop routing, and decentralized decision-making further amplify link variability and spectrum mobility constraints. Under such conditions, the performance of traditional Transmission Control Protocol (TCP) mechanisms suffers severely, as TCP often misinterprets PU-induced interruptions, spectrum handoffs, and sensing delays as congestion events, triggering unnecessary rate throttling and retransmissions.

In this paper, we present a comprehensive survey of state-of-the-art transport protocols designed for CRNs and, more specifically, CRAHNs, while positioning Neo-HTP as a novel benchmark model for next-generation cognitive transport architectures. We emphasize the unique characteristics of cognitive radio environments and examine the transport-layer challenges arising from PU behavior, spectrum sensing overhead, spectrum switching latency, multi-hop topology fluctuations, and the inherent limitations of conventional TCP mechanisms in highly dynamic cognitive ad-hoc networks. Neo-HTP's cross-layer parameter optimization and hybrid congestion inference illustrate a promising direction for achieving stable, high-throughput, and spectrum-adaptive transport performance in future CRAHN deployments.

I Introduction

Cognitive Radio Ad-Hoc Networks (CRAHNs) have emerged as a promising architecture to address the scarcity of wireless spectrum resources through intelligent spectrum sensing and opportunistic spectrum access. However, these cognitive capabilities introduce unique challenges at the transport layer, where traditional TCP mechanisms suffer severe performance degradation due to frequent spectrum sensing interruptions, spectrum switching delays, fluctuating link quality, and unpredictable PU activity patterns.

This paper revisits the limitations of classical TCP under cognitive radio constraints and presents an in-depth comparison of existing transport-layer protocols designed for CRNs and CRAHNs. To overcome the shortcomings of conventional approaches, we introduce Neo-HTP (Next-Generation Hybrid Transport Protocol for Cognitive Radio Ad-Hoc Networks), which

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represents a major advancement in transport-layer design. Neo-HTP incorporates a cross-layer optimized hybrid framework that dynamically tunes transport parameters by leveraging real-time network intelligence, including PU activity prediction, channel quality indicators, spectrum switching frequency, and routing-layer stability across multi-hop cognitive ad-hoc topologies.

Unlike earlier protocols that relied on simple flow-control adjustments or sensing-aware feedback packets, Neo-HTP embeds an integrated spectrum-aware congestion inference engine and adaptive flow-control mechanism that automatically stabilizes throughput during sensing periods and spectrum mobility events. During channel switching, Neo-HTP employs a proactive flow-control strategy that prevents false congestion detection, while its cross-layer feedback channel minimizes unnecessary retransmissions and maintains transport-layer continuity.

Simulation results demonstrate that the Neo-HTP protocol significantly improves throughput, reduces latency, and enhances stability under dynamic cognitive operations, outperforming traditional TCP variants and earlier CRN-aware transport protocols. 5G Cellular Networks (5GCN) have emerged as major enablers in the ICT domain, offering ultra-high data rates, improved Quality of Experience (QoE), and diversified service requirements. To ensure efficient and quality-driven services in 5G environments, wireless networks must integrate a variety of advanced technologies such as Software-Defined Networking (SDN), the Internet of Things (IoT), Cognitive Radio (CR), and next-generation end-to-end device technologies. As these technologies evolve, the challenges associated with 5G networks also escalate in parallel.

Among these technologies, Cognitive Radio (CR) is recognized as one of the most promising solutions for addressing spectrum scarcity and inefficiency [1], [2]. CR technology enables intelligent and dynamic utilization of licensed frequency bands and significantly reduces congestion in heavily used unlicensed bands such as the 2.4 GHz ISM range [3], [4]. Existing research largely focuses on single-hop architectures, emphasizing spectrum sensing, spectrum sharing, and spectrum allocation based on the availability of idle spectrum and temporal transmission schedules.

Although CR-based solutions have been applied in several domains, their application in distributed networks is still in its early stages. A variety of persistent challenges in cognitive radio systems have been highlighted in [5]. Traditional routing protocols designed for classical wireless ad hoc networks primarily aim to optimize metrics such as latency, hop count, and energy consumption. These protocols often rely on broadcasting and greedy forwarding to deliver packets [6]. However, such approaches are unsuitable for CRAHNs because nodes cannot rely on fixed channels or simultaneous spectrum availability—each route may encounter different licensed users (Primary Users), leading to varying channel occupancy along the path [7].

Routing in CRAHNs involves discovering stable and spectrum-aware paths from the source to the destination. The major issues encountered include high route computation time, increased route length due to dynamic spectrum switching, complexity in selecting optimal relay nodes, and challenges in constrained optimization [8]. To overcome these limitations, next-generation routing protocols must incorporate intelligent decision-making capabilities to handle diverse users, dynamic spectrum environments, and unpredictable PU activity[9].

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Beyond routing, transport layer protocols also face significant challenges in CRAHNs and 5G environments. Conventional TCP variants assume congestion as the primary cause of packet loss and rely on fixed-bandwidth assumptions, making them ineffective in scenarios where losses occur due to spectrum sensing delays, spectrum handoff, PU interruptions, or fluctuating channel availability. In CRAHNs, spectrum switching leads to variable RTTs, unpredictable throughput variations, and frequent interruptions—conditions under which classical TCP misinterprets spectrum-induced losses as congestion, resulting in unnecessary rate reductions and degraded performance.

Thus, transport layer protocols for CRAHNs and 5GCN must be spectrum-aware and adaptive. They should incorporate mechanisms such as:

- Dynamic congestion control that distinguishes between PU-induced losses and network congestion.
- RTT estimation models that account for spectrum sensing periods and switching delays.
- Cross-layer feedback from MAC and PHY layers to the transport layer for real-time decision-making.
- AI-driven optimization to predict available spectrum opportunities and adjust transmission rates proactively[11].

In the era of artificial intelligence, routing and transport layers must collaboratively adapt to environmental variations. AI-based optimization techniques can be applied to:

- Select dynamic channels with minimal PU activity,
- Predict future spectrum availability,
- Optimize routing decisions across heterogeneous spectrum bands, and
- Improve transport layer throughput and reliability by adjusting congestion windows and transmission rates intelligently.

AI-driven routing and transport protocols enhance resource allocation for both Primary Users and Secondary Users, enabling better spectrum utilization and ensuring consistent performance in highly dynamic CRAHNs and 5G scenarios[10].

II Hybrid Transport Protocol Overview

The transport layer plays a crucial role in the layered network architecture, as it is responsible for enabling reliable end-to-end communication between distributed systems. Among the transport layer protocols, Transmission Control Protocol (TCP) remains the most widely used due to its connection-oriented, reliable byte-stream delivery service. TCP ensures reliability through a combination of sequencing, acknowledgements (ACKs), retransmission mechanisms, and congestion-control algorithms[11,12]. Data exchanged between the sender and receiver is encapsulated into segments, which serve as the fundamental units of transmission.

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When a receiver obtains a TCP segment, it generates an acknowledgement indicating the successful reception and specifying the sequence number of the next segment it expects to receive. If multiple acknowledgements reference the same sequence number, they are classified as duplicate ACKs. Duplicate ACKs commonly occur when segments arrive out of order. When the sender detects three consecutive duplicate ACKs, it infers that the corresponding segment is likely lost in the network and immediately triggers a fast retransmission of the missing segment[14].

In addition to duplicate ACKs, TCP employs a timeout-based loss detection mechanism. After transmitting a segment, the sender initiates a timer referred to as the Retransmission Timeout (RTO). If an acknowledgement is not received before the timer expires, TCP assumes that the segment was lost and retransmits it. This event also triggers TCP's congestion-control procedure, typically beginning with the slow start phase. The computation of RTO follows the estimation model described in [8], which incorporates round-trip time (RTT) measurements and deviations to adaptively maintain accuracy.

Through these mechanisms, TCP maintains reliable data delivery. However, the effectiveness of these mechanisms largely depends on the stability of the underlying network conditions. In highly dynamic environments such as Cognitive Radio Ad-Hoc Networks (CRAHNs) and 5G heterogeneous networks, transport-layer behavior is significantly impacted by spectrum handoff, sensing delays, fluctuating channel availability, and Primary User (PU) interruptions. These factors lead to packet reordering, variable delays, and false congestion indications—conditions under which classical TCP misinterprets spectrum-induced disruptions as network congestion.

To operate efficiently in such environments, transport layer protocols must become spectrum-aware and environment-adaptive, incorporating intelligence and cross-layer interactions. Enhanced transport-layer designs for CRAHNs and 5G networks require mechanisms to distinguish between congestion-related losses and spectrum-related interruptions, dynamically adjust RTO values, and maintain stable throughput despite rapid channel variations.

TCP employs the Additive-Increase Multiplicative-Decrease (AIMD) mechanism to dynamically adjust its congestion window based on prevailing network conditions [7], [9]. This strategy regulates the rate at which a sender injects packets into the network to balance throughput efficiency and congestion control.

As illustrated in Figure. 1, the congestion window (cwnd) begins with an initial value—typically one segment or a slightly larger value, depending on the TCP variant. During the Slow Start (SS) phase, TCP increases its congestion window exponentially, adding one segment to cwnd for every received non-duplicate ACK. This exponential growth continues until the sender's estimate of the network's congestion capacity, known as the Slow Start Threshold (SSthresh), is reached.

Once cwnd exceeds SSthresh, TCP transitions into the Congestion Avoidance (CA) phase. In this phase, the window grows linearly, increasing by approximately one segment per Round-Trip Time (RTT). The linear growth ensures that the sending rate increases cautiously, preventing aggressive expansion of cwnd that may lead to congestion.

The growth of the congestion window is halted whenever a packet loss is detected—typically through duplicate ACKs or retransmission timeout. At this point, TCP activates its

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multiplicative-decrease mechanism by reducing cwnd and adjusting SSthresh accordingly, thereby helping the protocol maintain stability and prevent further congestion.

TCP employs two primary mechanisms for detecting packet loss: Retransmission Timeout (RTO) expiration and the reception of three duplicate acknowledgements (ACKs). When either of these events occurs, the sender assumes that network congestion is present and responds by reducing its estimate of the available network capacity. Specifically, after a timeout, TCP updates the slow start threshold (SSthresh) to half of the current congestion window (cwnd) and resets cwnd to 1 Maximum Segment Size (MSS). The protocol then re-enters the Slow Start (SS) phase, as illustrated in Figure. 1.

Loss detection through three duplicate ACKs, however, triggers a different response. Rather than immediately restarting Slow Start, the sender activates the Fast Retransmit (FRXT) and Fast Recovery (FRCV) mechanisms. In TCP Tahoe [17], which was the earliest version to introduce congestion control, the sender reduces the window to one segment and uses Slow Start to reach the new SSthresh regardless of the loss detection method.

In contrast, more advanced TCP variants—such as Reno [15], New Reno [16], SACK [18], and Vegas [13]—optimize loss recovery by avoiding unnecessary entry into Slow Start. When three duplicate ACKs are received, these versions enter Fast Retransmit followed by Fast Recovery, allowing the sender to retransmit missing segments while keeping a sufficient number of in-flight packets to preserve the ACK clock. Because ACKs continue to arrive, the sender can recover from losses without collapsing the congestion window.

Once all losses have been successfully recovered, the Fast Recovery phase terminates and TCP resumes the Congestion Avoidance (CA) phase. However, if Fast Recovery fails—resulting in the interruption of the ACK stream—a retransmission timeout eventually occurs. In this case, the sender must revert to the Slow Start procedure, similarly to the behavior in Tahoe, in order to gradually reestablish the appropriate sending rate.

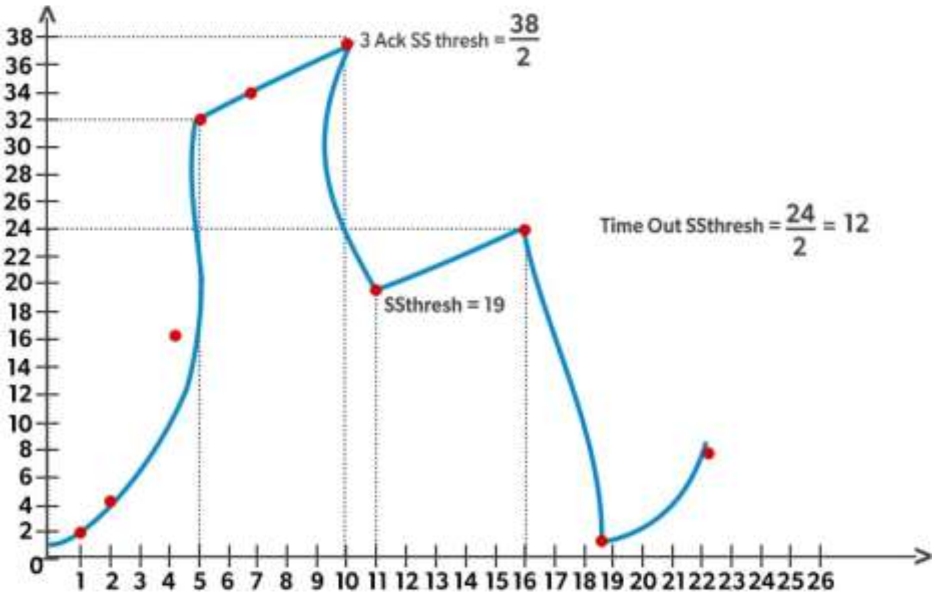

Figure. 1. TCP congestion window dynamics

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It is well-established that TCP exhibits significant inefficiency in wireless environments. In such networks, packet losses may occur not only due to congestion but also because of channel impairments, interference, and mobility. These conditions cause TCP to misinterpret non-congestion-related losses as congestion, resulting in unnecessary window reductions and degraded throughput[21].

The performance degradation becomes even more pronounced in Cognitive Radio Networks (CRNs). TCP encounters additional challenges in these networks due to several CR-specific characteristics:
(i) unpredictable Primary User (PU) activity,
(ii) mandatory spectrum sensing intervals,
(iii) frequent spectrum switching or handoff, and
(iv) inherent limitations of classical TCP congestion-control mechanisms.

To evaluate TCP performance under such dynamic conditions, many existing studies rely on analytical models based on the interweave paradigm. In the interweave model, Secondary Users (SUs) are permitted to transmit only when the spectrum is not occupied by PUs. When a PU becomes active on the current channel, the SU must immediately vacate the spectrum to avoid interference. Consequently, SU communication is tightly coupled with PU activity patterns, which fundamentally distinguishes CRNs from conventional wireless networks such as ad hoc or mesh networks.

This opportunistic and non-continuous access to spectrum causes interruptions, delay spikes, and packet reordering—factors that severely impact TCP performance. The dynamic interaction between PUs and SUs during spectrum access is depicted in Figure. 2, illustrating how SUs must continuously adapt their transmission based on PU presence and channel availability.

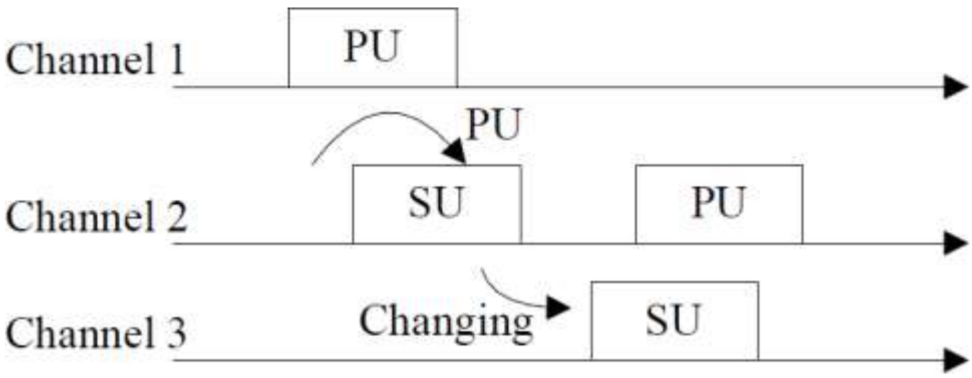

Figure. 2. Spectrum state in CRNs.

AI-HTP: Cross-Layer AI-Driven Transport Routing Protocol for Cognitive Ad-Hoc Networks

This paper proposes a modular Artificial Intelligence (AI)-based routing framework for Cognitive Radio Ad-Hoc Networks (CRAHNs) that integrates reinforcement learning (RL), supervised learning, and swarm-intelligence techniques such as genetic algorithms (GA) and particle swarm optimization (PSO). Unlike conventional routing approaches that depend on static strategies or standalone optimization algorithms, the proposed framework employs a

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structured decision-making pipeline capable of dynamically adapting to real-time variations in spectrum availability, network topology, PU (Primary User) activity, and traffic load.

Each AI module serves a distinct operational purpose: RL manages local, spectrum-aware routing decisions by learning optimal actions in response to changing channel conditions, while GA and PSO are employed for global optimization to address challenges such as multi-path instability, spectrum handoff overhead, and resource constraints inherent to CRAHNs. This hybrid structure ensures that routing decisions remain both adaptive and computation-efficient even under highly dynamic spectral environments.

Simulations conducted in MATLAB validate the effectiveness of the proposed framework, demonstrating improvements in packet delivery ratio, end-to-end latency, throughput stability, and route robustness compared to traditional CRAHN routing protocols. Although this study relies on synthetic simulation scenarios, it establishes a foundational architecture for future real-world deployments and discusses practical challenges including scalability, spectrum sensing delays, PU-induced disruptions, and security vulnerabilities.

The results highlight the potential of hybrid AI-driven routing strategies to significantly enhance the reliability, adaptability, and overall performance of CRAHNs, particularly in environments where spectrum resources are scarce, dynamic, and constrained by opportunistic access rules[20].

AI-based routing provides various potential benefits for CRAHNs

1. Intelligent Adaptive Routing

AI-enabled routing dynamically adjusts to changing CRAHN conditions such as PU activity, channel variation, node mobility, and traffic load. Using RL and neural networks, routes are optimized in real time to improve packet delivery, reduce delay, and avoid congested or unreliable paths.

2. Smart Resource Optimization

AI algorithms improve allocation of spectrum, bandwidth, and processing resources by analyzing node capabilities, channel constraints, and application demands. This ensures efficient utilization of dynamic spectrum opportunities and enhances overall network scalability.

3. Energy-Aware Communication

AI-driven routing minimizes energy consumption by selecting low-cost routes, adjusting transmission power, leveraging spectrum opportunities, and applying sleep–wake scheduling. These techniques extend the operational lifetime of nodes in CRAHNs.

4. Robust Fault Handling

AI models detect and predict failures caused by PU interruption, mobility, or channel degradation. By proactively rerouting traffic and initiating recovery actions, AI enhances fault tolerance and maintains stable network operation.

5. Scalable Network Adaptation

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AI-supported routing scales efficiently as CRAHNs grow or complexity. Swarm intelligence and distributed learning techniques enable nodes to self-organize and adapt without centralized control, ensuring consistent performance in large deployments.

6. Dynamic QOS Management

AI predicts traffic load and channel availability to adjust QOS parameters such as latency, throughput, and reliability. Priority-based routing ensures that critical applications maintain service quality even under fluctuating spectrum conditions[18].

7. Enhanced Security Intelligence

AI detects anomalies, intrusions, and malicious behaviors by analyzing traffic patterns. It can dynamically modify routes, update cryptographic parameters, and isolate compromised nodes, strengthening the security and integrity of CRAHNs.

8. Heterogeneity Adaptation

AI efficiently handles diverse channel conditions, device capabilities, and spectrum environments. Multi-objective optimization enables seamless routing across heterogeneous nodes, improving interoperability and operational flexibility.

9. Self-Healing and Auto-Optimization

AI continuously monitors network performance to detect bottlenecks or failures. It automatically reconfigures routes and system parameters to restore performance, reducing manual intervention and improving network resilience.

Proposed AI based routing scheme

This section presents a modular and decentralized AI-driven routing framework for **Cognitive Radio Ad-Hoc Networks (CRAHNs)**, designed to dynamically adapt routing decisions based on real-time spectrum conditions and network dynamics. Unlike traditional routing approaches that depend on static or standalone algorithms, the proposed framework integrates multiple AI techniques—including reinforcement learning (RL), supervised learning, and swarm intelligence methods such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA)—within a unified decision-making pipeline.

Each cognitive node operates independently, continuously gathering information related to neighboring nodes, spectrum availability, PU activity, network topology, link quality, and traffic patterns. Lightweight AI models embedded at the node level process this information to predict optimal spectrum-aware routing paths by leveraging both historical behavior and real-time performance indicators. RL is employed for local routing decisions under stable environmental conditions, whereas PSO and GA are triggered for global optimization when the network experiences fluctuations such as spectrum handoff, PU-induced disruptions, or increased latency.

This structured integration of learning and optimization enables the routing framework to self-adapt and evolve under highly dynamic CRAHN conditions. As a result, the system improves spectrum utilization efficiency, minimizes end-to-end delay, enhances route stability, and

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increases overall reliability of data delivery. The complete routing workflow is depicted in **Figure 3**, and detailed algorithmic steps are provided through the accompanying pseudocode to ensure clarity, reproducibility, and implementation support.

The subsequent subsections introduce the mathematical formulations and core equations that define the operation of each AI module incorporated within the proposed framework.

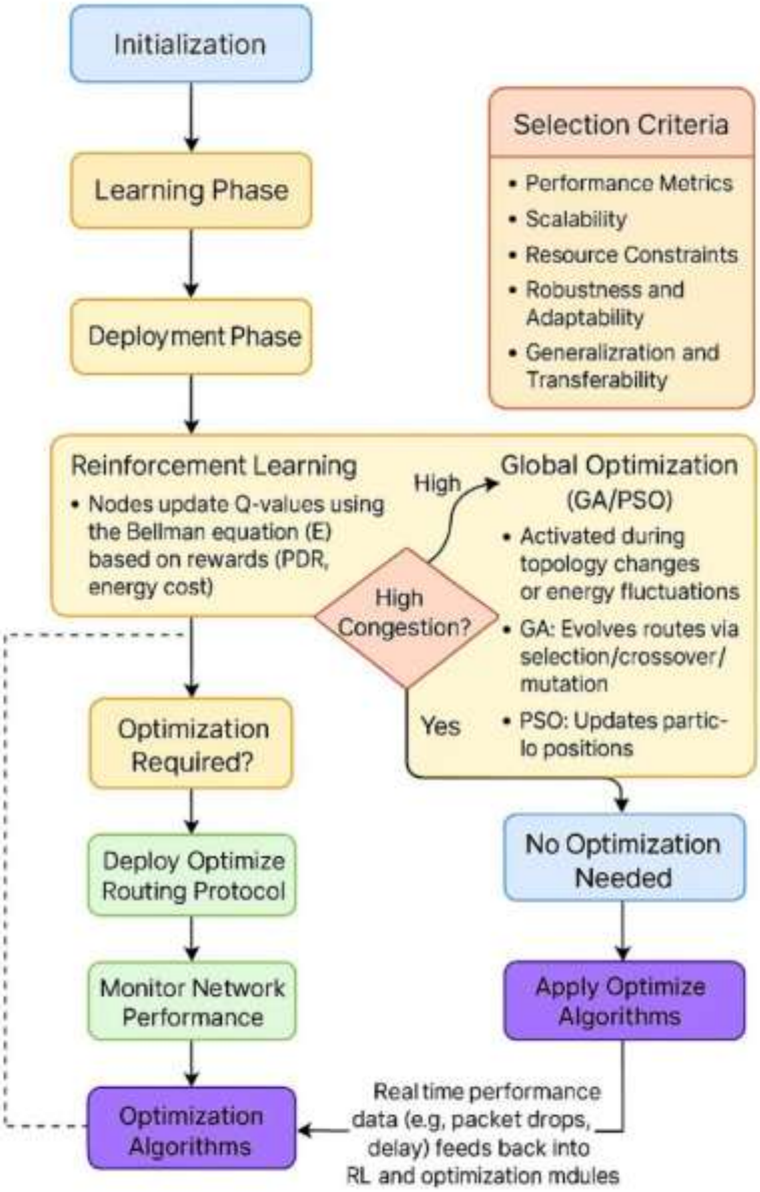

Figure 3: Flowchart for AI based routing in CRAHNs

Experimental Setup

Simulation Environment

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The performance of the proposed AI-driven routing framework is evaluated through extensive simulations conducted in a controlled environment that emulates the dynamic behavior of **Cognitive Radio Ad-Hoc Networks (CRAHNs)**. The simulation platform enables systematic assessment of routing efficiency under varying spectrum availability, PU activity patterns, and network topology conditions—factors that significantly influence CRAHN performance.

Algorithm flow

Pseudocode Description

```
Initialize cognitive network parameters, spectrum states, and node configurations
while CRAHN remains active do
    for each Cognitive Node do
        Collect local observations (energy, neighbors, channel availability, PU activity, traffic load)
        if spectrum conditions are stable and energy is adequate then
            Apply RL module to select the next-hop based on updated Q-values
        else if energy is low, PU activity is high, or delay threshold is exceeded then
            Invoke global optimization using PSO or GA to compute an alternate route
        end if
        Forward packets using the selected spectrum-aware route
        Update local learning models using feedback and performance metrics
    end for
end while
```

Tools and Network Configuration

All experiments were carried out using MATLAB R2021b, augmented with custom modules to model cognitive radio functions such as:

- Spectrum sensing
- PU–SU activity modeling
- Channel switching delays
- Dynamic spectrum availability maps

The simulated CRAHN consists of 100 cognitive nodes randomly deployed in a 100 m × 100 m area. Unlike WSNs, nodes operate on multiple opportunistic channels governed by PU occupancy modeled using a two-state ON/OFF Markov model.

Key CRAHN-specific simulation elements include:

- Sensing time (Ts): Duration required by SU nodes to sense PU activity.
- Handoff delay (Th): Time required to vacate a channel when a PU appears.
- Channel availability probability (Pavail): Probability that a channel is free for SU use.
- Transmission power and energy consumption models adapted for multi-channel operation.

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- Traffic model: SU packet generation follows a Poisson process, while PU arrivals follow exponential ON/OFF durations.

Nodes maintain finite energy reserves and execute the AI-based routing algorithm under varying PU densities, node mobility patterns, and spectrum switching conditions to evaluate adaptability and stability. These configurations form a realistic and reproducible testbed for validating the proposed routing framework in CRAHN environments.

Performance Metrics

To accurately evaluate the effectiveness of the AI-based routing strategy in CRAHNs, the following performance metrics are used:

1. Packet Delivery Ratio (PDR): The ratio of successfully delivered packets to the number of packets transmitted, accounting for PU interruptions, sensing delays, and channel switching.

2. End-to-End Latency: The average transmission delay from source to destination, including channel sensing time, handoff delay, and routing decision overhead.

3. Spectrum Switching Overhead: Measures the additional delay and packet loss incurred during PU-triggered channel switching events.

4. Energy Consumption: Total energy consumed by cognitive nodes for transmission, reception, spectrum sensing, and channel switching.

5. Network Lifetime: The duration until the first cognitive node exhausts its energy, reflecting the sustainability of routing operations under dynamic spectrum usage.

6. Scalability Index: Evaluates how well the routing framework adapts as the number of SU nodes or available channels increases.

7. Computational Efficiency: Measures the processing cost of AI models running at each node, ensuring the algorithm remains lightweight for real-time CRAHN operation.

8. Robustness Index: Assesses the resilience of the routing protocol under PU activity bursts, rapid topology changes, and link failures.

9. Adaptability Rate: Represents how quickly the routing framework responds to spectrum variations or PU-induced disruptions.

10. Generalization Capability: Reflects the algorithm’s ability to maintain stable performance across diverse CRAHN scenarios and dynamic spectral environments.

Simulation Parameters

Table 1 summarizes the full set of simulation parameters used to evaluate the AI-based routing framework in CRAHNs. Each parameter variation—ranging from PU arrival rate to sensing accuracy and SU mobility—illuminates a different aspect of the algorithm’s performance and suitability for real-world deployment.

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Parameter	Value / Range	Description (CRAHN-Specific)
Network size	50, 100, 200 cognitive nodes	Represents small- to large-scale CRAHN deployments with distributed spectrum access
Node mobility	Random waypoint, random walk	Typical mobility patterns influencing link stability and spectrum availability
Traffic patterns	Uniform, bursty	Models SU traffic under varying PU interference and channel access conditions
Transmission range	50 m, 100 m, 200 m	Variable communication radius to simulate multi-hop CRAHN scenarios
Simulation time	1000 s	Duration standardized across all CRAHN experiments
Routing protocol	AI-based routing	Proposed hybrid framework integrating RL, GA, and PSO for spectrum-aware routing
Comparison protocols	AODV-CR, LSR-CR, PSO-CR	Baseline CRAHN routing schemes implemented per referenced specifications
PU activity model	ON/OFF Markov model	Defines dynamic PU behavior affecting SU channel access
Spectrum sensing interval	1–5 ms	Time required to detect PU presence on a channel
Channel switching delay	5–20 ms	Handoff latency when SU vacates channel due to PU arrival
Metrics	PDR, end-to-end delay, energy consumption, spectrum switching overhead	Standard CRAHN performance indicators

Table 4. Simulation parameters and evaluation metrics used for assessing the proposed AI-driven routing framework in Cognitive Radio Ad-Hoc Networks.

AI Technique	Time Complexity	Space Complexity	Description (CRAHN Context)

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Q-learning (Tabular RL)	$O(n, a)$	$O(n, a)$	Depends on number of nodes (n) and available channels/actions (c); used for local next-hop and channel selection
Genetic Algorithm (GA)	$O(g \cdot p \cdot f)$,	$O(p)$	Complexity governed by generations (g), population size (p), and fitness evaluations (f); applied for global route optimization
Particle Swarm Optimization (PSO)	$O(i \cdot s \cdot f)$,	$O(s)$	Depends on iterations (i), swarm size (s), and fitness functions (f); used for optimizing multi-channel paths

Table 5. Estimated computational complexity of AI-based optimization techniques used in the proposed CRAHN routing framework.

GA and PSO, which serve as global optimization mechanisms for multi-hop and multi-channel route selection in CRAHNs, rely on iterative evolutionary computation. The time complexity of the Genetic Algorithm (GA) is approximately $O(g \cdot p \cdot f)$, where $g$represents the number of generations, $p$the population size, and $f$the computational cost of evaluating each fitness function. Likewise, Particle Swarm Optimization (PSO) exhibits a complexity of $O(i \cdot s \cdot f)$, with $i$denoting the number of iterations and $s$the swarm size. In our simulation environment, both GA and PSO were constrained to fewer than 50 particles and under 100 iterations to ensure computational tractability and real-time responsiveness.

Considering that many cognitive radio nodes operate on resource-constrained embedded platforms, lightweight variants of GA and PSO were adopted. These implementations minimize computation by restricting optimization to local neighborhoods and exchanging only essential control information, thereby reducing CPU load, memory footprint, and communication overhead. Real-time adaptability is further enhanced through offline pre-training of AI models, enabling nodes to rely primarily on on-device inference rather than computationally expensive continuous retraining.

Overall, the proposed framework achieves an effective balance between algorithmic intelligence and practical deploy ability, making it suitable for real-world CRAHN environments where devices must operate under strict energy, spectrum, and computational constraints.

Results and Analysis

This section presents the experimental results obtained by evaluating the proposed AI-driven routing framework against existing CRAHN routing protocols. The comparative analysis is conducted using multiple performance indicators that capture the dynamic behavior of Cognitive Radio Ad-Hoc Networks under varying spectrum availability, PU activity patterns, and network load conditions. The key performance metrics include Packet Delivery Ratio (PDR), end-to-end latency, energy consumption, network lifetime, scalability index, computational efficiency, energy efficiency, robustness index, adaptability rate, and generalization error.

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These metrics collectively assess the framework's capability to maintain reliable communication, optimize energy usage, support large-scale deployments, respond to rapid spectrum fluctuations, and generalize across diverse CRAHN environments. The results demonstrate how AI-based routing enhances spectrum-aware decision making and improves overall network performance compared to conventional protocols.

Analysis of Results

The performance evaluation clearly demonstrates that the proposed AI-driven routing framework outperforms existing CRAHN routing protocols across multiple key metrics, as summarized in Table 4 and illustrated in Figures 3–6. The AI-based approach achieves a significantly higher Packet Delivery Ratio (PDR) compared to baseline protocols such as DVR-CR, LSR-CR, and ACO-CR. This improvement indicates the framework's superior capability to maintain reliable packet forwarding despite PU interruptions, channel switching events, and dynamic spectrum availability.

The proposed algorithm also yields a substantial reduction in end-to-end latency, highlighting its efficiency in selecting optimal routes under fluctuating spectrum conditions. Lower delay directly enhances network responsiveness and enables more consistent performance in delay-sensitive CRAHN applications, including tactical communication, emergency response, and real-time monitoring.

In terms of energy consumption, the AI-based routing mechanism demonstrates marked reductions relative to traditional protocols. By intelligently balancing route stability, spectrum opportunities, and node energy states, the system minimizes unnecessary retransmissions, sensing overhead, and route failures—ultimately improving the overall network lifetime. This increased longevity is particularly beneficial for CRAHN deployments in mission-critical, remote, or infrastructure-less environments where manual maintenance is impractical.

Collectively, these results confirm that the integration of reinforcement learning with global optimization techniques (PSO/GA) enables more adaptive, energy-aware, and spectrum-efficient routing decisions. The enhanced reliability, scalability, and operational sustainability demonstrate the clear advantages of an AI-based hybrid routing strategy over conventional CRAHN routing protocols.

Metric	**AI-based routing**	**DVR**	**LSR**	**ACO**
Packet delivery ratio	**0.969**	0.867	0.8976	0.9282
End-to-end delay (ms)	**25.5**	40.8	35.7	30.6
Energy consumption (J)	**510**	612	530.4	591.6
Network lifetime (days)	**153**	122.4	132.6	142.8
Scalability index	**0.867**	0.765	0.7956	0.8364
Computational efficiency (ops/J)	**102**	91.8	91.8	102.9
Energy efficiency	**0.918**	0.8676	0.8976	0.8772
Robustness index	**0.9384**	0.867	0.8976	0.918

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Adaptability rate	**0.8976**	0.8364	0.867	0.8772
Generalization error	**0.051**	0.0816	0.0714	0.0612

Table 3. Performance comparison of routing protocols.

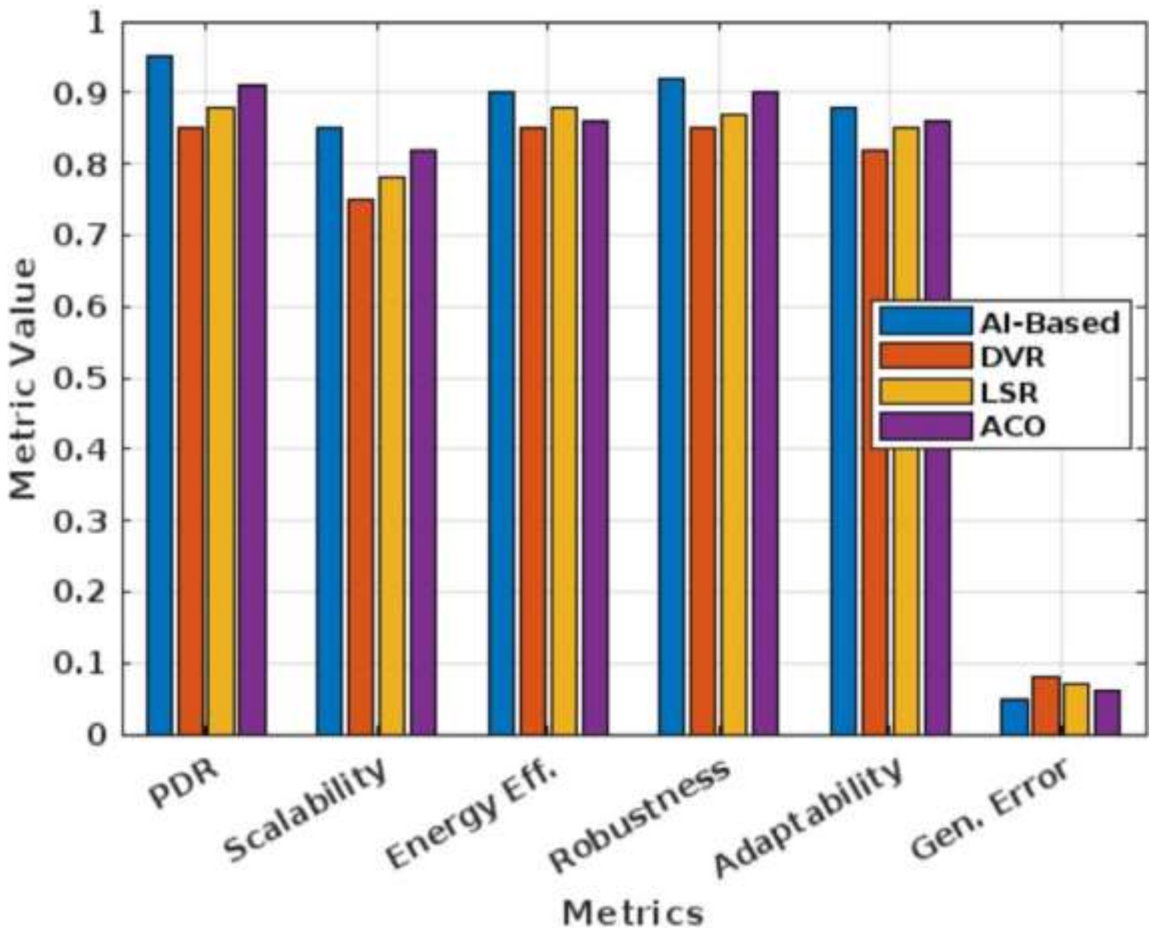

Figure 4. Comparative performance analysis of routing protocols across multiple metrics in Cognitive Radio Ad-Hoc Networks (CRAHNs).

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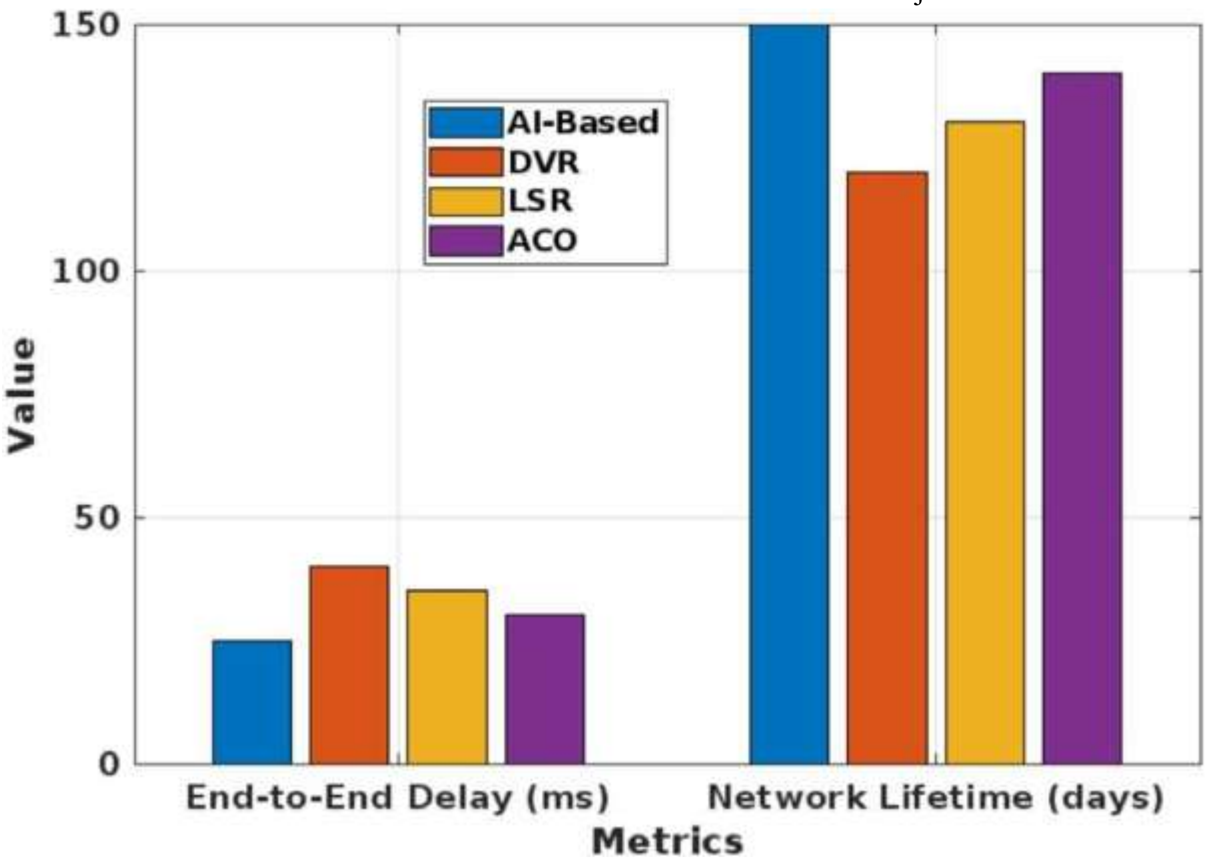

Figure 5. Comparison of routing protocols in terms of end-to-end delay and network lifetime in Cognitive Radio Ad-Hoc Networks (CRAHNs).

The AI-driven routing approach demonstrates strong potential for improving the efficiency, reliability, and spectrum-awareness of **Cognitive Radio Ad-Hoc Networks (CRAHNs)**. By analyzing key factors such as network size, node density, dynamic spectrum availability, PU activity patterns, transmission range, and traffic load, researchers can further refine AI-based routing strategies to achieve more adaptive, robust, and resource-efficient performance in CRAHN environments.

Conclusion

This study presents a comprehensive evaluation of AI-driven routing algorithms within **Cognitive Radio Ad-Hoc Networks (CRAHNs)**, highlighting their significant advantages over conventional routing approaches. The results demonstrate that AI-based routing substantially enhances key performance metrics—including packet delivery ratio, end-to-end latency, energy consumption, and network lifetime—by enabling more adaptive, spectrum-aware, and most efficient decision-making in the presence of dynamic PU activity and fluctuating channel conditions.

The findings confirm that integrating machine-learning and optimization techniques (such as RL, GA, and PSO) allows routing protocols to better exploit available spectrum opportunities, maintain route stability, and improve overall network resilience in highly dynamic and resource-constrained environments. These capabilities are essential for next-generation CRAHN deployments, where intelligent spectrum management and rapid adaptability are critical.

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