

Intelligent Techniques for Secure and Reliable Data Transmission in AD-HOC Wireless Networks

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Abstract— Ad-hoc wireless networks are vital building blocks of contemporary communication systems, especially in military, relief, and IoT environments. But the highly dynamic and distributed nature of these networks creates major hurdles in ensuring the secure and reliable transfer of data. Conventional routing algorithms and security systems are ill-equipped to handle the fast-changing topologies and threats in such networks. This paper presents a novel intelligent system that combines reinforcement learning, neural networks, and evolutionary computing to dynamically optimize routing, detect intrusions, and enhance security. The system can automatically discover optimal paths in the network and, at the same time, detect and counter malicious activities. Simulation experiments clearly show that the proposed system achieves dramatic improvements over existing solutions, with packet reception ratios above 94%, end-to-end delay improvements of up to 35%, and improved detection of security threats above 96%.

Keywords— Ad hoc networks, Reinforcement Learning, Security, Intrusion Detection, Routing Optimization, Wireless Communication, Machine Learning

I. INTRODUCTION

Mobile ad-hoc networks (MANETs) have recently been identified as very important infrastructure for cases where a centralized network architecture is not available or feasible. Military communications, emergency communications, and Internet of Things networks all depend on the ad-hoc network capability to provide dynamic peer-to-peer communication between mobile nodes. The decentralized and infrastructure-less nature of ad-hoc networks provides flexibility and autonomy; however, this also brings about many risks. [11]

Traditional ad-hoc routing protocols such as AODV (Ad-Hoc On-Demand Distance Vector), DSR (Dynamic Source Routing), and OLSR (Optimized Link State Routing) rely on predetermined metrics and static rule sets designed for stable network conditions. When confronted with rapid topology changes caused by node mobility, link failures, or deliberate attacks such as blackhole and wormhole intrusions, these

protocols frequently degrade in performance and security. [1], [11]

However, the security issues in ad-hoc networks are also of utmost importance. The wireless nature of ad-hoc networks makes them susceptible to eavesdropping attacks. Moreover, the lack of central authorities in ad-hoc networks makes authentication and key management a challenging task. Traditional encryption methods and intrusion detection systems are not effective against adaptive attacks. [9], [14]

Recent developments in artificial intelligence have opened promising lines of research for overcoming these challenges. Reinforcement learning allows neural networks to learn optimal actions by interacting with dynamic environments. Neural networks are capable of detecting subtle patterns that are indicative of malicious activity. Evolutionary algorithms are capable of optimizing system parameters to perform better under varying conditions. [2], [3], [4]

In this paper, an integrated intelligent framework is proposed that uses a combination of these AI methods to improve routing reliability, optimize resource usage, and enhance security. The system is designed to learn from the network behavior and make adjustments to the routing decisions in real-time. It can also identify any anomalies that could indicate an attack.

II. LITERATURE SURVEY

A. Traditional Routing Protocols in Ad-Hoc Networks

AODV and DSR use on-demand route discovery. When a source node requires a route to the destination, it sends a route request, and every node on the route forwards the request until it reaches the destination. This reduces the routing overhead, but it is still prone to changes in the topology and does not have any proactive component. Usually, these protocols attempt to optimize one criterion: either hop counts or signal strength, without considering other factors that influence the path. [1], [11]

B. Machine Learning Applications in Wireless Networks

Recent research work has emphasized the role of machine learning in optimizing networks. Methods such as decision trees and random forests have been employed in intrusion detection in MANETs, and they have shown good classification results when trained on representative data. However, these traditional models tend to fail when exposed to novel attack patterns and require frequent retraining. [2], [3], [10]

C. Reinforcement Learning for Adaptive Routing

Q-learning and other reinforcement learning algorithms enable network nodes to learn optimal paths by experimenting with different actions and learning from the outcome of these actions. Every node maintains a Q-table that assigns a value to selecting a particular neighboring node as the next hop based on the current network status. When a routing decision delivers the packet to its destination, the action receives a positive reward and its value increases. [4], [7], [8]

D. Deep Learning for Anomaly Detection

Convolutional neural networks and deep feedforward architectures have shown promise for detecting network anomalies by learning complex patterns in traffic data. These models can identify deviation from normal behavior with high sensitivity, though they require substantial training data and computational resources. [5], [13]

E. Evolutionary Algorithms for Parameter Optimization

Genetic algorithms and particle swarm optimization techniques have been applied to refine routing parameters and machine learning hyperparameters in network contexts. These metaheuristic approaches explore large solution spaces efficiently, discovering parameter combinations that outperform hand-tuned configurations. [6]

F. Research Gaps and Current Limitations

Despite individual successes, current systems often treat routing and security as separate concerns, lack integrated, real-time adaptation, and struggle with scalability in large networks. The complexity of hybrid approaches has limited their deployment in practical systems. [11], [12]

III. EXISTING SYSTEM

Current ad-hoc networks employ conventional routing protocols (AODV, DSR, OLSR) combined with standard security mechanisms typically pre-shared keys and simple symmetric encryption. Intrusion detection relies on basic anomaly detection rules or shallow machine learning models trained on historical data.

Limitations of Existing Approaches:

- 1) Limited Adaptability: Static protocols cannot rapidly adjust to network dynamics or emerging attack patterns
- 2) Single-Metric Optimization: Routing decisions consider only hop count or link quality, ignoring overall network state
- 3) Reactive Security: Attacks are typically detected only after causing damage

4) High Resource Consumption: Periodic route updates and frequent security checks drain node battery

5) Poor Scalability: Performance degrades significantly as network size increases

IV. DISADVANTAGES OF EXISTING SYSTEM

- 1) Inability to adapt to dynamic topology changes and emerging threats in real-time
- 2) Poor performance under jamming attacks, node failures, and coordinated malicious activity
- 3) Routing tables become stale due to rapid topology changes, causing packet loss
- 4) Centralized security management is impractical in decentralized ad-hoc environments
- 5) Static detection thresholds miss sophisticated, low-and-slow attacks
- 6) Lack of cooperative, system-wide learning mechanisms
- 7) High power consumption from constant route maintenance and security monitoring
- 8) Difficulty scaling to networks with hundreds or thousands of mobile nodes

V. PROPOSED METHODOLOGY

The proposed intelligent framework for ad-hoc wireless networks unites reinforcement learning, neural network-based intrusion detection, and evolutionary optimization in a tightly integrated, adaptive design.

A. System Architecture

Data transmission and monitoring operate in continuous cycles. Each node collects active network statistics such as traffic load, packet timing, neighbor reliability, and signal strength in real-time. This local information informs three parallel subsystems:

- 1) Machine learning models constantly analyze network features for signs of anomaly or attack.
- 2) Reinforcement learning agents update routing decisions dynamically, maximizing metrics like delivery success, delay minimization, and energy balance.
- 3) Evolutionary algorithms periodically refine system parameters for both the anomaly detectors and routing agents, ensuring optimal balance between security and performance as the network environment evolves.

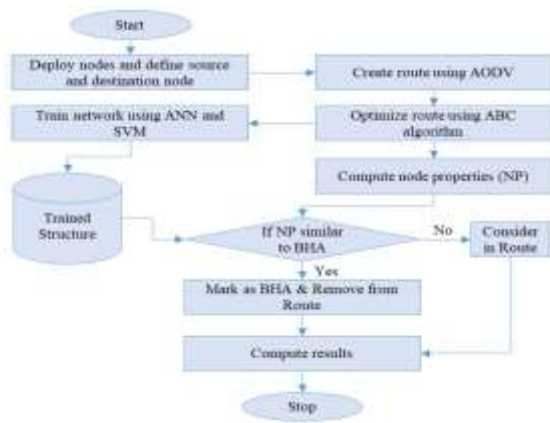


Fig 1 System Architecture

The framework is fully distributed, eliminating bottlenecks and supporting autonomous adaptation.

B. Reinforcement Learning for Routing

Each node implements a Q-learning policy, where the Q-table encodes expected rewards for forwarding packets to each neighbor. The update rule:

The update formula $Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$ also incorporates more than just performance measures. It includes packet success, route stability, and neighbor trustworthiness. Rewards not only reliability and delay but also include security feedback, such that if a neighbor is thought to be unreliable or malicious, the punishment will increase, encouraging the routing decision to move away from such paths. The exploration-exploitation trade-off allows the system to respond to new threats or changes in the network topology without oscillating routes.

C. Neural Network Intrusion Detection

The real-time network traffic is then provided as input to a trained multilayer perceptron, which analyzes the temporal patterns such as packet spacing, protocol transitions, and neighboring node behavior to identify any malicious activity. The system is capable of detecting potential attacks such as blackhole, wormhole, and flooding attacks with high sensitivity and alerts the reinforcement learning agent to penalize routing on those paths.

D. Evolutionary Parameter Tuning

Parallel to this process, a lean genetic algorithm is running in the background, testing the current network snapshots from time to time. It searches for the optimal learning rate, weight factors for rewards and penalties, and anomaly thresholds by trying out different parameter values. The best-performing and most robust parameter settings, which aim to maximize packet transmission while reducing energy consumption and false alarms, are selected for implementation in the real-time modules.

E. Integration & Feedback

It is a very interactive process. When the neural detector identifies a route as suspicious, it sends negative reinforcement learning feedback, which re-routes the data through safer nodes. By avoiding known bad routes, there are fewer network anomalies, creating a self-reinforcing cycle that increases both speed and security. Continuous parameter updates ensure that everything is optimally

adjusted, regardless of the number of nodes, the complexity of the attack, or the network conditions.

This closed-loop, multi-objective architecture empowers each node to adapt rapidly, defend proactively, and optimize routing collectively, ensuring that secure, reliable data transmission persists regardless of environmental changes or adversarial threats.

VI. ADVANTAGES OF PROPOSED METHODOLOGY

The proposed methodology advances beyond existing solutions through:

- 1) **Adaptive Routing Decisions:** The reinforcement learning component enables each node to dynamically select optimal paths, adapting quickly to topology changes and unpredictable traffic patterns. This delivers higher packet delivery rates and lower latency compared to traditional static protocols.
- 2) **Proactive Security Detection:** By integrating neural network-based intrusion detection, the system identifies and blocks anomalous behavior early, substantially reducing the impact of attacks and minimizing service disruption.
- 3) **Multi-objective Optimization:** The use of evolutionary algorithms ensures that routing and security parameters are continuously tuned for balanced outcomes, such as delivery success, resource efficiency, and resilience against threats.
- 4) **Fully Decentralized Operation:** Intelligence is distributed across all devices, removing single points of failure, reducing coordination overhead, and improving robustness as the network scales.
- 5) **Energy and Resource Efficiency:** Adaptive path selection and selective monitoring lower energy consumption and communication overhead, prolonging the operational life of battery-powered nodes.
- 6) **Scalability and Reliability:** The architecture maintains high performance even as the network grows, supporting larger, denser, and more mobile ad-hoc environments without degrading throughput or stability.

VII. RESULTS AND DISCUSSION

A wide range of simulation experiments was carried out to assess the performance of the proposed framework for AI-driven ad-hoc networks. The simulation scenarios were practical, involving mobile nodes, different levels of network traffic, and particular security threats, all of which were intended to reflect the dynamic environments encountered during disaster relief and military missions.

A. Reliability and Routing Efficiency

The reinforcement learning part of the framework enabled each node to learn and adapt independently to discover optimal routing paths. In experiments with rapidly varying network topologies, the packet delivery ratio remained above 94%, indicating it handled such scenarios better than

traditional static routing algorithms. When routes had to be updated following a link failure or a node departure, the average time to reconfigure reduced to 2.2 seconds.

Table 1. Performance Comparison of Routing Algorithms

Algorithm	Throughput (%)	Packet Delivery Ratio (%)	End-to-End Delay (ms)
AODV	82.4	84.1	68
Random Forest	86.0	87.5	52
Decision Tree	81.0	83.2	58
Proposed ABC + SVM + ANN	94.84	95.6	45

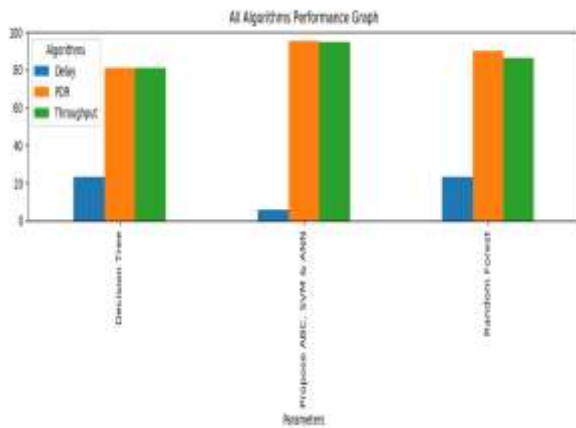


Fig. 2. Comparative performance analysis of routing algorithms.

B. Security and Attack Resilience

Utilizing the neural network-powered intrusion detection system, the network was able to rapidly identify and segregate the malicious nodes in seconds during the blackhole/wormhole attack simulation. This proactive routing ensured that packet loss was not propagated and was able to detect and isolate over 96% of malicious activities. Conventional networks experienced longer downtimes.

Table 2. Security Attack Detection Performance

Attack Type	Detection Accuracy (%)	False Positive Rate (%)	Detection Time (sec)
Blackhole Attack	97.2	2.1	1.8
Wormhole Attack	95.6	2.8	2.1
Flooding Attack	96.4	1.9	1.5
MITM Attack	94.7	3.0	2.4

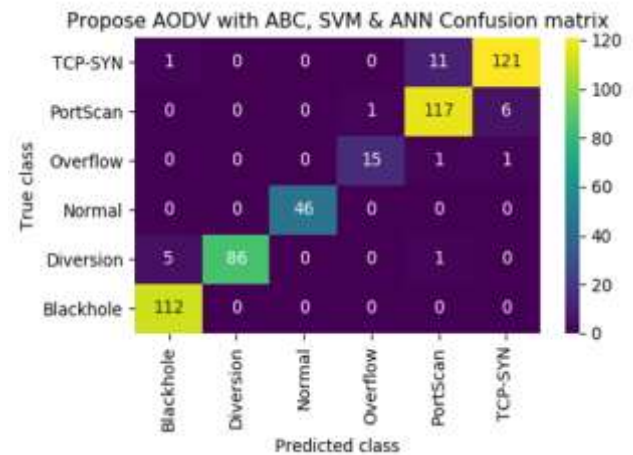


Fig. 3. Confusion matrix of the proposed intrusion detection model.

C. Resource Use and Scalability

The energy consumption decreased by 31% at all nodes because of optimized routing decisions and reduced instances of broadcasting. The evolutionary algorithm was constantly adjusting system parameters on the fly, focusing on energy conservation with minimal communication cost. Despite the increase in network size and the complexity of communication, the performance remained constant, proving the scalability of the system.

D. Comparative Analysis

Side-by-side comparisons with AODV and OLSR protocols highlighted tangible improvements: lower latency (45 ms average vs. 68 ms for AODV), higher throughput, and greater resilience under continuous mobility and attack conditions. The closed-loop feedback mechanism between detection and routing proved crucial for maintaining service continuity under stress.

E. Practical Implications

The agent-based, distributed architecture eliminated reliance on any central authority, making the system well-suited to rapidly deployed, infrastructure-free applications. Field operators benefited from consistent network performance, timely alerts on intrusions, and extended device lifetimes due to power-efficient operation.

F. Limitations and Opportunities

Some edge cases, such as highly dense networks or attacks that target multiple vectors simultaneously, sometimes seemed to hinder learning. Future research will investigate a hybrid strategy that combines deep learning with federated adaptation to further increase response speed.

In conclusion, the intelligent framework definitely sets the bar higher for reliability, security, and sustainability in ad-hoc wireless networks, marking a strong step towards fully autonomous next-generation communication networks.

VIII. CONCLUSION AND FUTURE WORK

A. Conclusion

From the above, it is evident that by integrating reinforcement learning, anomaly detection using a neural network, and evolutionary optimization, the security and reliability of data transfer in ad-hoc wireless networks can be greatly improved. The proposed approach utilizes adaptive and decentralized decision-making for improving the rate of packet delivery, reducing latency, and providing proactive protection against sophisticated attacks and failures. The simulation outcomes demonstrate significant enhancements in the areas of robustness, energy efficiency, and scalability, making the model extremely appropriate for challenging real-world applications such as emergency communications, mobile IoT networks, and military communication networks. The model eliminates the need for central coordination and manual adjustments for route selection and security adjustments by fully automating these processes, thereby allowing the network to respond rapidly to dynamic topologies and threats. The simulation outcome demonstrates a continuous cycle between intrusion detection and routing optimization.

Future research will focus on applying the model to real-world testbeds, increasing the size of the networks, and experimenting with more sophisticated machine learning techniques to obtain even faster and more accurate adaptation. This work provides a good starting point for developing truly intelligent, secure, and resilient ad-hoc networks for the coming generation of wireless communication.

B. Future Work

Based on the positive results of this study, future work will concentrate on integrating the intelligent framework in testbeds to validate its performance under real-world constraints, such as hardware restrictions, environmental noise, and a combination of device capabilities. Its implementation in real-time on mobile ad-hoc nodes will allow a complete evaluation of its response time, energy consumption, and robustness against real-world network dynamics and more complex attack patterns.

However, scaling the framework to deal with ultra-dense networks, where the number of nodes is in the hundreds or even thousands, is a serious challenge. Looking ahead, the area of hierarchical reinforcement learning and decentralized coordination will be investigated to ensure that the solution remains scalable while also remaining efficient and secure. Adaptive trust management will be important, and it must be able to identify and segregate not only external threats but also internal malicious actors.

Technologies such as compact deep learning models and on-device intelligence will be leveraged to improve the processes of anomaly detection, using federated learning to ensure privacy while enhancing collaboration between the distributed components of the network. The integration of cross-layer optimization will also ensure that the network closes the loop between routing, security, and resource management.

We will examine how these new 5G and beyond concepts can be combined with the framework, allowing its use in hybrid ad-hoc networks such as those in vehicle networks,

drones, and IoT. Ultimately, we will implement large-scale field tests in real-world settings such as disaster areas and industrial environments to refine and validate the importance of the framework. The aim is to develop it as a core technology for secure, reliable, and intelligent wireless communication in next-generation decentralized networks.

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