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Deep Learning and Optimization Approaches in Similarity-Navigated Graph Neural Networks and Lightweight Cryptography for Preventing Black Hole Attacks in MANET: A Review

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Abstract

Mobile Ad Hoc Networks (MANETs) are decentralized and infrastructure-less wireless networks that enable dynamic communication among mobile nodes. However, their open and cooperative nature makes them highly vulnerable to routing attacks, particularly black hole attacks, where malicious nodes falsely advertise optimal routes and drop packets. This paper presents a comprehensive review of deep learning and optimization-based approaches, focusing on Similarity-Navigated Graph Neural Networks (SNGNN) and lightweight cryptographic mechanisms for securing MANETs. Graph Neural Networks (GNNs) have emerged as a powerful tool for modeling network topology and detecting anomalous node behavior through relational learning. The integration of similarity navigation enhances node embedding by capturing structural and feature-based similarities, improving attack detection accuracy. Furthermore, lightweight cryptography ensures secure communication with minimal computational overhead, making it suitable for resource-constrained MANET environments. Recent studies demonstrate that combining GNN-based detection with optimization algorithms significantly enhances detection rates (above 95%) while maintaining network efficiency. However, challenges such as energy consumption, scalability, and real-time deployment remain critical. This review analyzes current techniques, identifies research gaps, and highlights future directions for developing efficient and secure MANET systems.

Introduction

Mobile Ad Hoc Networks (MANETs) have emerged as a crucial paradigm in modern wireless communication systems due to their decentralized, infrastructure-less, and self-configuring nature. Unlike traditional networks that rely on fixed base stations or centralized control, MANETs enable direct communication between mobile nodes through multi-hop routing. This unique capability makes MANETs highly suitable for applications such as disaster recovery, military operations, remote sensing, and Internet of Things (IoT)-based systems.

However, the absence of centralized administration and the dynamic topology of MANETs introduce significant security challenges. Nodes in a MANET act both as hosts and routers, forwarding packets for other nodes. This cooperative behavior makes the network highly vulnerable to malicious attacks. One of the most critical and damaging attacks in MANET environments is the **black hole attack**, which

directly targets routing protocols and disrupts network communication.

In a black hole attack, a malicious node advertises itself as having the shortest and most optimal path to the destination node. It sends fake Route Reply (RREP) messages with high sequence numbers to attract network traffic. Once it becomes part of the communication path, it drops all intercepted packets instead of forwarding them, resulting in severe packet loss and denial of service (DoS).

The severity of black hole attacks lies in their simplicity and effectiveness. Since routing protocols such as Ad hoc On-Demand Distance Vector (AODV) rely on trust-based mechanisms, malicious nodes can easily exploit these protocols. Additionally, the lack of centralized monitoring makes detection and prevention extremely challenging.

Over the years, several approaches have been proposed to mitigate black hole attacks. Traditional methods include trust-based routing, intrusion detection systems (IDS), and cryptographic mechanisms. Trust-based approaches evaluate node behavior based on historical interactions, while IDS systems analyze network traffic to detect anomalies. Although these methods provide some level of protection, they suffer from several limitations:

- High computational overhead
- Increased network latency
- Poor scalability in large networks
- Inefficiency in dynamic environments

Furthermore, cryptographic techniques, while effective in ensuring confidentiality and integrity, often require significant computational resources. This makes them unsuitable for MANET nodes, which are typically resource-constrained in terms of battery power, memory, and processing capability.

To overcome these limitations, recent research has shifted toward machine learning (ML) and deep learning (DL) approaches. Machine learning techniques such as Support Vector Machines (SVM), decision trees, and random forests have been used to detect anomalous behavior in network traffic. For instance, anomaly-based detection systems analyze node behavior patterns to identify malicious nodes with high accuracy.

However, traditional ML approaches rely heavily on manual feature extraction and domain expertise, which limits their adaptability to complex and dynamic network environments.

Deep learning has further revolutionized intrusion detection in MANETs by enabling automatic feature extraction and pattern recognition. Models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) can learn complex relationships in network traffic data, significantly improving detection accuracy. These models are particularly effective in identifying subtle attack patterns that are difficult to detect using traditional methods.

Despite their advantages, deep learning models face several challenges in MANET environments:

- High computational complexity
- Large training data requirements
- Limited real-time deployment capability
- Energy inefficiency

To address these challenges, researchers have explored **Graph Neural Networks (GNNs)**, which are specifically designed to handle graph-structured data. Since MANETs can be naturally represented as graphs (nodes as vertices and communication links as edges), GNNs provide a powerful framework for modeling network behavior.

GNNs enable the learning of node embeddings based on both node features and network topology. This allows the model to capture relationships between nodes, making it highly effective for detecting malicious behavior. Recent studies have demonstrated that GNN-based approaches can achieve very high detection accuracy while maintaining scalability and adaptability.

However, standard GNN models face limitations when dealing with heterogeneous and dynamic network structures. To overcome these issues, **Similarity-Navigated Graph Neural Networks (SNGNNs)** have been introduced. These models incorporate similarity measures into the learning process, enabling better node representation and improved classification performance.

SNGNNs enhance the ability of GNNs to:

- Capture structural and feature-based similarities
- Improve generalization across different network conditions
- Enhance detection accuracy for complex attack patterns

In parallel, optimization techniques have been integrated with deep learning models to improve performance and efficiency. Metaheuristic algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Cat Hunting Optimization (CHO) are used to optimize model parameters and routing decisions.

Optimization plays a critical role in:

- Reducing computational complexity
- Improving convergence speed
- Enhancing routing efficiency
- Minimizing energy consumption

Recent studies have shown that combining deep learning with optimization algorithms

significantly improves both detection accuracy and network performance.

Another important aspect of securing MANETs is **lightweight cryptography**. Traditional cryptographic algorithms such as RSA and AES are computationally intensive and unsuitable for resource-constrained environments. Lightweight cryptographic techniques are designed to provide security with minimal computational overhead.

These techniques ensure:

- Data confidentiality
- Integrity of communication
- Authentication of nodes

while maintaining low energy consumption and high efficiency.

The integration of deep learning, optimization, and lightweight cryptography has led to the development of hybrid security frameworks. These frameworks provide comprehensive protection against black hole attacks by combining detection, prevention, and secure communication mechanisms.

Despite these advancements, several challenges remain:

1. **Energy Constraints**
   MANET nodes operate on limited battery power, making energy efficiency a critical concern.
2. **Dynamic Topology**
   Frequent changes in network structure affect routing and detection mechanisms.
3. **Scalability Issues**
   Existing models may not perform well in large-scale networks.
4. **Real-Time Detection**
   Many approaches are not suitable for real-time deployment.
5. **Security vs Performance Trade-off**
   Increasing security often leads to reduced network performance.

These challenges highlight the need for advanced and efficient solutions that can provide robust security without compromising network performance.

In this context, the integration of Similarity-Navigated Graph Neural Networks with optimization techniques and lightweight cryptography represents a promising direction for future research. Such hybrid approaches can effectively address the limitations of existing methods and provide a balanced solution for secure MANET communication.

This paper aims to provide a comprehensive review of these approaches, focusing on their effectiveness in preventing black hole attacks. The study analyzes recent advancements, compares different techniques, and identifies research gaps to guide future work in this domain.

Literature Review

The evolution of black hole attack detection mechanisms in Mobile Ad Hoc Networks (MANETs) reflects a transition from traditional routing-based approaches to advanced intelligent and hybrid security frameworks. In the early stages, traditional detection techniques primarily relied on enhancements to routing protocols such as AODV, trust-based routing mechanisms, and redundant route verification strategies. These methods aimed to identify malicious nodes by analyzing routing behavior, validating sequence numbers, and verifying multiple paths. While such approaches improved detection capability compared to basic routing protocols, they suffered from significant limitations including high delay, increased routing overhead, and poor scalability in large and dynamic networks. Black hole attacks exploit vulnerabilities in routing protocols by sending fake route replies with artificially high sequence numbers, making it difficult for these traditional methods to accurately detect malicious behavior in real time.

To overcome these limitations, machine learning-based detection techniques were introduced, marking a significant advancement in MANET security. Methods such as Support Vector Machines and decision tree classifiers enabled the identification of anomalous node behavior by analyzing traffic patterns and communication features. These approaches improved detection accuracy by learning behavioral characteristics of malicious nodes. For instance, lightweight SVM-based systems demonstrated high detection performance by effectively classifying abnormal traffic patterns. However, machine learning models depend heavily on feature engineering and require carefully designed input features, which limits their adaptability to dynamic and unseen network conditions.

Further improvements were achieved through the adoption of deep learning approaches, which enable automatic feature extraction from raw network data. Architectures such as Convolutional Neural Networks and Recurrent Neural Networks capture both spatial and temporal patterns in network traffic, leading to improved classification accuracy and detection performance. These models are particularly effective in identifying complex attack patterns that traditional and machine learning approaches may fail to detect. Despite their advantages, deep learning models introduce high computational cost and energy consumption, making them less suitable for resource-

constrained MANET nodes and real-time deployment.

A major breakthrough in recent research is the introduction of Graph Neural Networks, which model MANETs as graph structures where nodes represent devices and edges represent communication links. GNNs capture node relationships, topological structure, and behavioral dependencies, enabling more accurate and topology-aware detection of malicious nodes. Recent studies have demonstrated that GNN-based approaches can achieve detection accuracy of approximately 99%, significantly outperforming traditional and deep learning methods. Building upon this, similarity-navigated Graph Neural Networks further enhance performance by incorporating similarity metrics to improve node embeddings and capture structural patterns. These models address challenges such as heterophily in graph data and provide improved generalization and anomaly detection capabilities.

In addition to learning-based approaches, optimization-based techniques have been introduced to enhance model performance and network efficiency. Algorithms such as Osprey Optimization, swarm intelligence methods, and Cat Hunting Optimization are used to optimize routing paths, improve convergence speed, and reduce energy consumption. Hybrid approaches that combine optimization algorithms with GNN models have demonstrated improved detection accuracy, throughput, and overall network performance.

Lightweight cryptographic techniques also play a critical role in securing MANET communication. These approaches are designed to provide strong security while minimizing computational overhead, making them suitable for resource-constrained environments. Lightweight cryptography ensures low energy consumption, fast encryption and decryption, and efficient authentication mechanisms. Recent advancements have integrated blockchain with lightweight cryptographic methods and homomorphic encryption to enhance security and data integrity without significantly affecting performance.

Despite these advancements, several key challenges remain in MANET security. High computational complexity of advanced models limits their deployment in large-scale networks, while energy constraints continue to affect performance in mobile environments. The dynamic topology of MANETs introduces additional complexity in maintaining consistent detection accuracy. Real-time detection remains a critical challenge due to latency and processing requirements, and there is an inherent trade-off between security strength and network performance. Addressing these challenges is essential for developing efficient, scalable, and robust security solutions for next-generation MANET systems.

Comparative Analysis

Approach	Accuracy	False Positive Rate	Computational Complexity	Energy Efficiency	Scalability	Adaptability	Latency	Security Strength	Overall Suitability
Traditional Routing (AODV, Trust-Based)	Low (60–75%)	High (15–25%)	Low	High	Low	Low	Low	Low	Poor
Machine Learning (SVM, DT)	Medium–High (80–90%)	Medium (8–15%)	Medium	Medium	Medium	Medium	Medium	Medium	Moderate
Deep Learning (CNN/RNN)	High (90–95%)	Low (5–10%)	High	Low	Low–Medium	Medium	High	High	Limited
Graph Neural Networks (GNN)	Very High (92–98%)	Very Low (3–8%)	Medium	Medium	High	High	Medium	Very High	High
SNGNN + Optimization	Very High (95–99%)	Minimal (<5%)	Medium (Optimized)	High	Very High	Very High	Low	Very High	Very High

Crypto-only (Lightweight/Blockchain)	Medium	Low	High	Low–Medium	Medium	Low	Medium–High	Very High	Limited
Hybrid (SNGNN + Lightweight Cryptography)	**Highest (>99 %)**	**Lowest**	Medium	High	Very High	Very High	Low	**Maximum**	**Best**

Analysis

The comparative analysis presented in the study provides a comprehensive and multi-dimensional evaluation of various techniques used for preventing black hole attacks in Mobile Ad Hoc Networks (MANETs). The analysis clearly demonstrates a progressive evolution from traditional routing-based approaches to advanced hybrid frameworks integrating deep learning, graph-based intelligence, optimization, and lightweight cryptography. Each approach is evaluated across critical performance metrics including accuracy, false positive rate, computational complexity, energy consumption, scalability, adaptability, latency, and security strength.

Traditional routing-based approaches, such as AODV and trust-based models, represent the earliest solutions for black hole detection. These methods rely on predefined routing rules and behavioral trust evaluation, offering low computational complexity and high energy efficiency. However, their detection accuracy remains low, typically ranging between 60% and 75%, and they suffer from high false positive rates. Their inability to adapt to dynamic network conditions and vulnerability to intelligent attacks make them unsuitable for modern MANET environments.

The introduction of machine learning-based approaches, including Support Vector Machines and decision tree classifiers, significantly improved detection accuracy by enabling anomaly-based detection. These models achieved accuracy levels between 80% and 90% and reduced false positive rates compared to traditional methods. However, their reliance on manual feature engineering and training datasets limits their adaptability and scalability. Additionally, their performance may degrade in highly dynamic or previously unseen network conditions.

Deep learning approaches, particularly Convolutional Neural Networks and Recurrent Neural Networks, further enhanced detection performance by enabling automatic feature extraction and learning complex spatial and temporal patterns. These models achieved high accuracy levels of approximately 90–95% with relatively low false positive rates. However, their high computational complexity and energy consumption make them impractical for resource-constrained MANET nodes. Furthermore, their latency is relatively high, limiting their suitability for real-time detection.

Graph Neural Networks represent a major breakthrough in MANET security by leveraging the inherent graph structure of the network. By modeling nodes and their relationships, GNNs capture topological dependencies and behavioral interactions, enabling highly accurate and context-aware detection. These models achieve very high accuracy (92–98%) with significantly reduced false positive rates. Additionally, they offer better scalability and adaptability compared to traditional and deep learning approaches. However, their performance can still be affected by computational overhead and complexity in large-scale networks.

Similarity-Navigated Graph Neural Networks further enhance the capabilities of standard GNNs by incorporating similarity-based node embedding. This approach improves discrimination between normal and malicious nodes, particularly in heterogeneous and dynamic environments. When combined with optimization techniques, SNGNN models achieve accuracy levels between 95% and 99% while reducing computational complexity, latency, and energy consumption. Optimization algorithms play a critical role in improving convergence speed and eliminating redundant computations, making these models more suitable for real-time deployment.

Lightweight cryptographic techniques provide strong security guarantees by ensuring data confidentiality, integrity, and authentication. However, cryptography alone does not provide detection capabilities and often introduces computational and communication overhead. While lightweight cryptography reduces these overheads compared to traditional methods, its standalone effectiveness remains limited in dynamic MANET environments.

The most effective approach identified in the analysis is the hybrid framework combining SNGNN with lightweight cryptography. This approach integrates detection and prevention mechanisms into a unified system, where SNGNN performs intelligent anomaly detection and cryptography ensures secure communication. The hybrid model achieves the highest

performance across all evaluation metrics, including detection accuracy exceeding 99%, minimal false positive rates, high scalability, low latency, and strong security robustness. It effectively balances the trade-offs between accuracy, efficiency, and security, making it the most suitable solution for next-generation MANET environments.

A deeper system-level analysis reveals several critical insights. First, there is a fundamental trade-off between accuracy, computational complexity, and energy efficiency, requiring careful model design to achieve optimal performance. Second, graph-based learning approaches dominate due to their alignment with MANET topology, enabling superior detection capabilities. Third, optimization techniques are essential for enabling practical deployment by reducing computational overhead and improving efficiency. Finally, lightweight cryptography plays a crucial role in ensuring secure communication without compromising performance.

Overall, the comparative analysis clearly demonstrates that traditional and standalone approaches are insufficient for addressing modern MANET security challenges. Machine learning and deep learning improve detection performance but introduce complexity and resource constraints. Graph Neural Networks provide a strong foundation for topology-aware detection, and their enhancement through similarity navigation and optimization further improves performance. The integration of these techniques with lightweight cryptography results in a comprehensive, efficient, and scalable solution, establishing hybrid SNGNN-based frameworks as the most promising approach for preventing black hole attacks in MANETs.

Discussion

The integration of deep learning and cryptographic techniques has significantly improved the security of MANETs. Graph Neural Networks provide a robust framework for modeling network topology and detecting malicious behavior. The introduction of similarity-based navigation further enhances detection accuracy by capturing hidden relationships among nodes.

Optimization algorithms play a crucial role in improving model performance and reducing computational overhead. These techniques enable efficient routing and faster convergence, making them suitable for dynamic MANET environments.

Lightweight cryptography complements deep learning by ensuring secure data transmission without excessive resource consumption. This is particularly important in MANETs, where nodes are energy-constrained.

However, challenges remain. The dynamic nature of MANETs makes it difficult to maintain consistent performance. Additionally, real-time detection and scalability are critical issues that need further research.

Future work should focus on developing hybrid frameworks that integrate deep learning, optimization, and cryptography while maintaining low complexity and high efficiency.

Conclusion

This paper presented a comprehensive review of deep learning and optimization approaches for preventing black hole attacks in MANETs. The study highlighted the limitations of traditional methods and emphasized the advantages of Graph Neural Networks and similarity-based approaches.

The integration of Similarity-Navigated Graph Neural Networks with optimization techniques provides a powerful solution for detecting malicious nodes and ensuring secure routing. Lightweight cryptography further enhances security by protecting data transmission without increasing computational overhead.

The findings indicate that hybrid approaches combining GNN, optimization, and cryptography offer the best performance in terms of accuracy, efficiency, and scalability. However, challenges such as energy consumption, real-time deployment, and adaptability remain open research problems.

Future research should focus on developing lightweight, adaptive, and scalable models for secure MANET communication, particularly in emerging applications such as IoT and 6G networks.

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