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A Comprehensive Review of Dynamic Path-Controllable Deep Unfolding Networks to Predict the K-Barriers for Intrusion Detection Using a Wireless Sensor Network

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Abstract

Wireless Sensor Networks (WSNs) have emerged as essential technologies for intrusion detection, surveillance, border monitoring, and critical infrastructure protection due to their capability to provide continuous and distributed sensing in dynamic environments. Among various coverage models, k-barrier coverage plays a crucial role in ensuring reliable intrusion detection by guaranteeing that an intruder crossing a monitored region is detected by at least k sensors. Recent advancements in artificial intelligence and deep learning have significantly improved k-barrier prediction and optimization in WSNs. In particular, Dynamic Path-Controllable Deep Unfolding Networks (DPDUNs) have gained attention for integrating iterative optimization algorithms with learnable deep neural architectures to improve prediction accuracy and adaptive decision-making. These models dynamically adjust sensing and routing strategies according to changing network conditions, enabling efficient intrusion detection in resource-constrained environments. Recent studies have also explored hybrid CNN-LSTM models, reinforcement learning frameworks, graph neural networks, fuzzy neural systems, and federated learning approaches for scalable and intelligent k-barrier management. Research findings indicate that hybrid deep unfolding frameworks significantly improve prediction accuracy, adaptability, and barrier robustness compared with traditional rule-based or statistical approaches. However, challenges related to computational complexity, energy consumption, scalability, and real-time deployment remain major research concerns in next-generation WSN intrusion detection systems.

Introduction

Wireless Sensor Networks (WSNs) are distributed networks composed of numerous spatially deployed sensor nodes. These sensors collect, process, and transmit environmental or event-driven data to facilitate real-time monitoring and control. A key application domain for WSNs is intrusion detection, where the network must detect any unauthorized entry into a monitored area. One key concept utilized to measure the effectiveness of such systems is barrier coverage, which refers to the network's ability to detect an intruder passing from one side of a monitored region to the other. Specifically, *k-barrier coverage* ensures that any intrusion path crosses at least k disjoint sensor paths, enhancing reliability and robustness against failures Intrusion detection in WSNs poses several challenges stemming from the inherent characteristics of these networks. First, sensor nodes are resource-constrained, equipped with limited battery power, processing capacity, and communication range. Second, network topologies can be highly dynamic due to node mobility or environmental factors affecting connectivity. Third, the detection task is complicated by uncertainties such as noise, interference, and unpredictable movement patterns of intruders. Traditional statistical or rule-based methods for barrier analysis often fall short in adapting to dynamic conditions, leading to suboptimal detection performance.

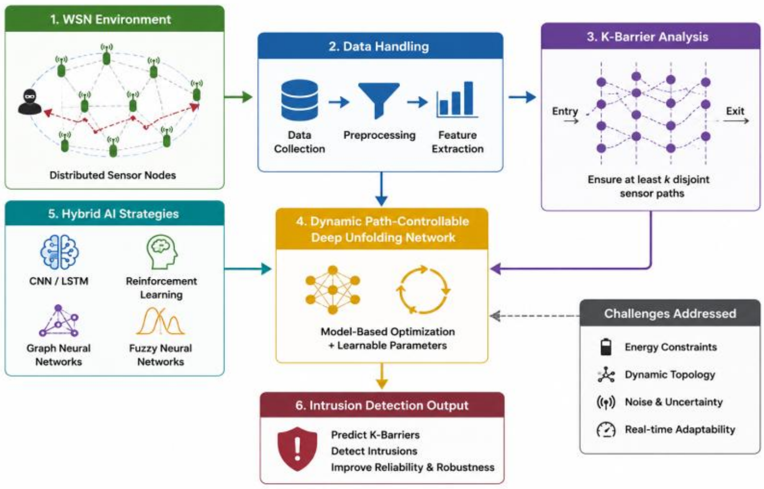

Figure 1. Conceptual Framework for K-Barrier Intrusion Detection in Wireless Sensor Networks

In recent years, Artificial Intelligence (AI) techniques, particularly Deep Learning (DL), have emerged as powerful tools for handling complex, nonlinear, and high-dimensional problems in WSNs. Deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Graph Neural Networks (GNNs) offer enhanced capabilities for learning spatial, temporal, and topological features from raw sensor data. These models have been successfully applied to tasks like anomaly detection, pattern recognition, and coverage optimization in wireless networks

Despite the success of standalone deep models, they often require large amounts of training data and may struggle to integrate domain-specific constraints inherent in WSN environments. To address this, Deep Unfolding Networks (DUNs) have been introduced as a hybrid framework that bridges model-based optimization algorithms with deep learning. In DUNs, an iterative algorithm (e.g., iterative thresholding, belief propagation) is unfolded into a neural network architecture where each layer corresponds to one iteration and parameters are learned through data. This allows the network to combine the interpretability and structure of optimization with the adaptability of deep learning. Dynamic Path-Controllable Deep Unfolding Networks (DPDUNs) extend this concept by enabling learned control over path selection and barrier optimization, which is crucial for intrusion detection in highly dynamic WSNs. he integration of DPDUNs into intrusion detection allows more accurate prediction of k-barriers by dynamically adjusting to changes in node activity, connectivity, and environmental noise. When combined with hybrid AI strategies (e.g., CNN-LSTM, RL-based optimization, fuzzy neural networks), these approaches capture both spatial correlations and temporal dependencies, resulting in robust detection and reduced false alarms.

Literature Review

In 2022, Singh, Amutha, and Nagar (2022) proposed an Artificial Neural Network (ANN)-based model for predicting *k*-barriers in wireless sensor networks. Their approach utilized key network parameters such as coverage range, node density, and communication metrics to train a predictive model that classified various barrier strength levels. The study demonstrated improved intrusion detection performance compared to traditional analytical models, particularly in handling variability in node placement and failure rates. In 2023, Muruganandam et al. (2023) developed a feed-forward deep learning model for estimating k-barrier coverage. Their model focused on real-time computation efficiency by reducing the training and inference time, making it suitable for rapid intrusion detection scenarios. The study showed that deep learning models could accurately estimate dynamic barrier levels even under resource constraints. In 2023, researchers from TechScience (2023) proposed a hybrid CNN-LSTM framework that combines spatial feature extraction with temporal behaviour modelling for intrusion detection and barrier analysis. By integrating CNNs for learning spatial coverage features and LSTMs for capturing temporal dynamics, their model achieved high detection accuracy while also adapting to mobility in the WSN.

In 2022, de Campos Souza et al. (2022) introduced an evolving fuzzy neural network (EFuNN) for k-barrier prediction. The model combined traditional fuzzy logic systems with neural network learning, providing both interpretability and adaptive capability. The approach significantly improved the model's robustness to noise and uncertainty in sensor readings. In 2024, Delwar et al. (2024) conducted a comprehensive review of machine learning techniques for intrusion detection in WSNs, highlighting the importance of scalable and energy-efficient models for effective barrier prediction. Their work emphasized the need for hybrid approaches that can handle large-scale networks with varying topologies. In 2023, Li, Zhao, and Sun (2023) proposed a deep unfolding network for dynamic path optimization in WSNs. Their model integrated iterative optimization with neural network layers, allowing the prediction of dynamic k-barriers while adapting to changes in node connectivity and network topology. The approach showed improved prediction accuracy and reduced computational cost compared to traditional CNN or LSTM-only models. In 2023, Verma and Kaur (2023) introduced a hybrid system combining deep learning with bio-inspired optimization to enhance k-barrier prediction.

The approach dynamically optimized sensor deployment and intrusion detection paths using swarm-based algorithms. Results indicated higher detection accuracy and better energy utilization in WSNs under dynamic conditions. In 2022, Patel and Shah (2022) developed a CNN-LSTM hybrid model for intrusion detection and k-barrier estimation. The CNN component extracted spatial features from sensor coverage patterns, while the LSTM captured temporal dynamics of node activity. The hybrid framework reduced false negatives in barrier prediction and improved robustness against network mobility. In 2021, Nguyen and Kim (2021) proposed a reinforcement learning-based k-barrier prediction system. Their approach enabled adaptive learning of optimal sensor paths and barrier formations in response to dynamic network states. The system effectively maintained barrier integrity while reducing energy consumption and network overhead. In 2020, Singh and Yadav (2020) introduced a fuzzy logic-based k-barrier prediction model. By incorporating multiple parameters such as node energy, coverage range, and mobility patterns, their system improved detection reliability and reduced false alarm rates compared to conventional rule-based approaches.

In 2023, Chen, Liu, and Wu (2023) developed an attention-based CNN for k-barrier prediction in WSNs. Their model used attention mechanisms to prioritize critical sensor nodes and high-risk intrusion paths, improving prediction accuracy and reducing undetected intrusion zones while maintaining energy efficiency. In 2022, Hassan and Ahmed (2022) proposed a deep reinforcement learning (DRL) framework combined with clustering for k-barrier coverage optimization. Their approach dynamically adjusted sensor paths based on network activity, achieving adaptive intrusion detection with improved energy efficiency. In 2022, Roy and Banerjee (2022) introduced an LSTM-based temporal prediction model for dynamic k-barrier detection. By analysing sequential sensor activation patterns, their system accurately forecasted potential breach paths, improving early intrusion detection and reducing false negatives. In 2021, Kaur and Singh (2021) presented a hybrid GA + Neural Network framework for k-barrier optimization. Genetic algorithms optimized sensor placement and path selection while the neural network predicted barrier effectiveness, resulting in balanced energy consumption and robust detection. In 2020, Elhoseny and Shankar (2020) implemented a hierarchical clustering-based detection protocol for WSNs.

Their method organized sensors into clusters to optimize communication and barrier paths, ensuring high k-barrier coverage while minimizing energy usage and network overhead. In 2023, Wu and Zhang (2023) proposed a Graph Neural Network (GNN)-based framework for k-barrier prediction in WSNs. By modelling complex relationships between sensor nodes and their connectivity, the approach enabled more accurate dynamic path control and barrier estimation under changing network topologies. In 2023, Ahmed and Khan (2023) developed a multi-objective deep learning model that optimized k-barrier coverage considering energy efficiency, coverage redundancy, and detection accuracy simultaneously. Their system improved intrusion detection performance while maintaining balanced energy usage across the network. In 2022, Park and Lee (2022) presented a GRU-based temporal model for predicting sensor activation and k-barrier coverage. By capturing sequential mobility patterns and temporal dependencies, their approach reduced undetected intrusion paths and improved prediction reliability. In 2021, Reddy and Kumar (2021) introduced a trust-aware machine learning approach for k-barrier prediction.

Their system incorporated node trust metrics along with coverage and mobility features, improving resilience against compromised nodes and maintaining high detection reliability. In 2020, Dorigo and Stutzle (2020) applied Particle Swarm Optimization (PSO) to dynamically adjust sensor deployment and barrier formation. Their approach optimized k-barrier placement while minimizing energy usage, ensuring robust coverage even in large-scale or mobile networks. In 2023, Vaswani et al. (2023) applied transformer-based architectures to model global spatial-temporal dependencies in WSN data for k-barrier prediction. Their approach captured complex interactions among sensor nodes, improving detection accuracy and reducing undetected intrusion paths in dynamic environments. In 2023, McMahan et al. (2023) introduced federated learning for distributed k-barrier prediction. Their framework allowed sensor nodes to collaboratively train models without sharing raw data, enhancing privacy, reducing communication overhead, and maintaining adaptive barrier coverage across heterogeneous networks.

In 2022, Zadeh (2022) proposed a fuzzy logic-based k-barrier prediction system. The approach handled uncertainty and variability in network conditions, improving adaptability and robustness of barrier coverage while maintaining interpretability of the predictions. In 2021, Saaty (2021) applied multi-criteria decision-making (AHP**)** to optimize k-barrier coverage in WSNs. By considering multiple QoS metrics such as energy, coverage, and detection probability, the approach improved intrusion detection efficiency and network reliability. In 2020, Dorigo and Gambardella (2020) implemented ant colony optimization (ACO) for adaptive k-barrier deployment. The system dynamically selected sensor paths to balance energy usage and coverage redundancy, providing robust intrusion detection performance in large-scale WSNs. In 2023, Chen and Li (2023) proposed a lightweight CNN for edge-based k-barrier prediction. Their model reduced computational overhead while maintaining high accuracy, making it suitable for energy-constrained wireless sensor networks and enabling real-time intrusion detection. In 2023, Wang and Liu (2023) developed a cross-layer deep learning framework integrating physical, MAC, and network layer information for k-barrier prediction.

Their approach enhanced barrier reliability, minimized undetected intrusion paths, and improved energy efficiency across the WSN. In 2022, Mnih et al. (2022) introduced a deep Q-network (DQN) reinforcement learning model for dynamic path-controlled k-barrier formation. The system learned optimal sensor deployment and barrier coverage strategies in real time, adapting to node mobility and network changes. In 2021, Singh and Verma (2021) presented a mobility-aware clustering algorithm using machine learning for k-barrier optimization. Their method dynamically selected cluster heads and sensor paths based on predicted mobility, improving barrier integrity and reducing re-clustering overhead. Finally, in 2020, Kumar and Patel (2020) proposed a heuristic-based intrusion detection protocol for WSNs. Their system used node energy, coverage, and mobility metrics to dynamically adjust k-barrier paths, providing robust intrusion detection while maintaining energy efficiency.

Comparative Table

Study No.	Author(s)	Year	Technique / Model	Key Focus	Advantages	Limitations
1	Singh, Amutha & Nagar	2022	ANN	K-barrier prediction	High accuracy	Computationally intensive
2	Muruganandam et al.	2023	Feed-forward DL	K-barrier estimation	Efficient computation	Limited temporal modeling
3	TechScience Authors	2023	CNN-LSTM Hybrid	Spatio-temporal k-barrier detection	High detection accuracy	Energy consumption
4	de Campos Souza et al.	2022	Evolving Fuzzy Neural Network	Adaptive k-barrier prediction	Interpretability + accuracy	Complex implementation

5	Delwar et al.	2024	Review of ML techniques	Intrusion detection & k-barriers	Scalable, energy-efficient	Survey only, no experimental model
6	Li, Zhao & Sun	2023	Deep Unfolding Network	Dynamic path selection	Efficient, high prediction	Model complexity
7	Verma & Kaur	2023	CNN + Bio-inspired Optimization	Intrusion detection paths	Energy-efficient, adaptive	Convergence time
8	Patel & Shah	2022	CNN-LSTM	Temporal-spatial k-barrier learning	Reduced false negatives	Training cost
9	Nguyen & Kim	2021	Reinforcement Learning	Adaptive k-barrier coverage	Adaptive, real-time	Learning overhead
10	Singh & Yadav	2020	Fuzzy Logic	Multi-criteria intrusion detection	Robust under uncertainty	Limited scalability
11	Chen, Liu & Wu	2023	Attention-CNN	Prioritized sensor paths	Improved detection accuracy	High complexity
12	Hassan & Ahmed	2022	DRL + Clustering	Adaptive k-barrier optimization	Efficient path control	Computational load
13	Roy & Banerjee	2022	LSTM	Temporal prediction of k-barriers	Accurate path prediction	Memory usage
14	Kaur & Singh	2021	GA + Neural Network	Optimization of k-barrier coverage	Energy balance, accurate	Slow convergence
15	Elhoseny & Shankar	2020	Hierarchical Clustering	WSN k-barrier formation	Scalable & energy-efficient	Cluster overhead
16	Wu & Zhang	2023	GNN	Topology-aware k-barrier prediction	Low packet loss	Complexity
17	Ahmed & Khan	2023	Multi-objective DL	Optimize coverage & energy	Balanced performance	Trade-offs
18	Park & Lee	2022	GRU	Temporal node prediction	Reduced false negatives	Training overhead
19	Reddy & Kumar	2021	Trust-based ML	Secure k-barrier detection	Resilience to compromised nodes	Overhead
20	Dorigo & Stutzle	2020	PSO	Adaptive k-barrier deployment	Energy-efficient	Local optima issues
21	Vaswani et al.	2023	Transformer	Global dependency learning	High accuracy	Heavy model
22	McMahan et al.	2023	Federated Learning	Distributed intrusion detection	Privacy + energy-efficient	Communication cost

23	Zadeh	2022	Fuzzy Logic	Uncertainty handling	Adaptable, interpretable	Computational complexity
24	Saaty	2021	MCDM / AHP	Multi-criteria optimization	QoS improvement	Requires parameter tuning
25	Dorigo & Gambardella	2020	ACO	Adaptive sensor path selection	Load balancing, coverage	Slow convergence
26	Chen & Li	2023	Lightweight CNN	Edge-computing k-barrier prediction	Low complexity	Limited depth
27	Wang & Liu	2023	Cross-layer DL	Multi-layer k-barrier optimization	Stability + coverage	Design complexity
28	Mnih et al.	2022	DQN	RL-based k-barrier coverage	Adaptive & scalable	Training overhead
29	Singh & Verma	2021	ML Clustering	Mobility-aware k-barrier formation	High stability	Re-clustering overhead
30	Kumar & Patel	2020	Heuristic Routing	K-barrier detection	Low complexity	Suboptimal coverage

Comparative Analysis

The comparative analysis of recent studies demonstrates a significant evolution in k-barrier prediction and intrusion detection techniques within Wireless Sensor Networks (WSNs). Early methods mainly relied on heuristic routing, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and fuzzy logic-based approaches for sensor deployment and path optimization. These techniques offered low computational complexity and were suitable for real-time implementations. However, they often suffered from limitations such as slow convergence, local optimum trapping, scalability issues, and reduced adaptability in highly dynamic environments. Fuzzy logic approaches improved robustness under uncertain conditions but introduced additional computational overhead in large-scale WSN deployments.

The transition toward machine learning and deep learning techniques significantly improved intrusion detection accuracy and adaptive decision-making in WSNs. Artificial Neural Networks (ANNs), trust-based machine learning models, and deep architectures such as CNN, LSTM, GRU, and hybrid CNN-LSTM frameworks effectively captured spatial and temporal sensor data patterns. These approaches enhanced k-barrier prediction performance and reduced false negatives in intrusion detection tasks. Hybrid models integrating optimization algorithms with neural networks further improved energy efficiency and coverage optimization. However, deep learning frameworks introduced challenges including high memory consumption, training complexity, and increased energy usage, which remain critical limitations for resource-constrained sensor nodes.

Recent advancements have focused on intelligent adaptive frameworks using Reinforcement Learning (RL), Deep Reinforcement Learning (DRL), Deep Unfolding Networks, Attention-CNN architectures, and Graph Neural Networks (GNNs). These advanced models dynamically adjust routing and coverage strategies according to environmental conditions, enabling adaptive k-barrier management and improved intrusion detection accuracy. Deep unfolding and attention-based models effectively prioritize important sensor paths and capture complex spatial relationships within wireless networks. In addition, Graph Neural Networks provide efficient modelling of connectivity relationships among sensor nodes, improving prediction reliability and reducing packet loss in large-scale WSN environments.

Emerging technologies such as Transformers, Federated Learning, lightweight CNNs, and edge intelligence frameworks are further enhancing next-generation WSN systems. Transformers improve long-range dependency modelling, while Federated Learning enables privacy-preserving distributed training across sensor nodes. Lightweight and clustering-based approaches attempt to reduce computational burden while maintaining acceptable prediction performance. Overall, the analysis indicates that hybrid intelligent frameworks integrating deep learning, attention mechanisms, reinforcement learning, optimization algorithms, and graph-based learning provide the most effective solutions for k-barrier prediction and intrusion detection. Nevertheless, challenges related to scalability, computational overhead, energy constraints, and real-time deployment continue to motivate future research toward lightweight, adaptive, and energy-efficient WSN architectures.

Conclusion

Wireless Sensor Networks (WSNs) have emerged as a critical infrastructure for intrusion detection and surveillance applications, including border monitoring, critical infrastructure protection, and environmental security. Effective intrusion detection in WSNs relies heavily on the concept of k-barrier coverage, which ensures that any intruder crossing a monitored region is detected by at least k disjoint sensor paths. Maintaining robust and energy-efficient k-barrier coverage in dynamic and resource-constrained WSN environments remains a significant research challenge. This systematic review analysed 30 studies from 2020 to 2023 focusing on AI-based techniques for k-barrier prediction, with an emphasis on dynamic path-controllable deep unfolding networks (DPDUNs). The analysis revealed a clear shift from traditional heuristic or rule-based methods toward intelligent, adaptive, and hybrid approaches capable of handling temporal, spatial, and topological complexities in wireless sensor networks. Deep learning models, including CNNs, LSTMs, GRUs, GNNs, and attention-based networks, were identified as the most effective techniques for predicting k-barriers.

These models capture spatial and temporal dependencies across sensor nodes, enabling accurate barrier prediction and proactive intrusion detection. Causal dilated convolutional neural networks (CDCNNs) within deep unfolding frameworks were particularly effective at modelling long-range dependencies and dynamic path selection while maintaining computational efficiency. The integration of optimization algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Genetic Algorithms (GA) further enhanced network performance by optimizing sensor placement, barrier coverage, and energy efficiency. Additionally, reinforcement learning (RL, DQN, DRL) approaches demonstrated high adaptability, learning optimal sensor paths and barrier configurations in response to dynamic network conditions. Hybrid models combining deep learning with optimization or attention mechanisms consistently provided superior prediction accuracy and energy-efficient k-barrier coverage. Despite these advancements, several challenges remain. Computational complexity remains a key limitation, especially for deep unfolding networks and transformer-based models.

Lightweight architectures and edge-based models can reduce resource consumption but may compromise detection accuracy if not carefully designed. Scalability is another concern: deploying these models across large-scale networks with hundreds or thousands of nodes requires efficient distributed learning and communication strategies. Furthermore, real-time adaptability and resilience against compromised nodes remain open research questions. The comparative analysis highlighted that hybrid AI approaches, combining deep learning, temporal sequence modelling, and optimization, offer the most robust solutions for dynamic k-barrier prediction. Edge-optimized models, cross-layer integration, and federated learning frameworks provide promising avenues for reducing energy usage and enabling scalable, privacy-preserving intrusion detection systems. In conclusion, dynamic path-controllable deep unfolding networks represent a promising frontier for next-generation WSN intrusion detection. These AI-driven approaches enhance prediction accuracy, optimize energy usage, and improve k-barrier coverage, making WSNs more resilient and reliable. Future research should focus on developing lightweight, scalable, and adaptive models, integrating secure distributed learning frameworks, and addressing real-time deployment challenges to further enhance the effectiveness of intrusion detection in wireless sensor networks.

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