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A Survey of Methods and Architectures for Dynamic Path-Controllable Deep Unfolding Network to predict the K-barriers for Intrusion Detection Using a Wireless Sensor Network

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Peer Review Information	Abstract
<p><i>Submission: 02 April 2025</i></p> <p><i>Revision: 23 April 2025</i></p> <p><i>Acceptance: 11 May 2025</i></p>	<p>Wireless Sensor Networks (WSNs) are critical in surveillance and intrusion detection systems, where reliable detection of unauthorized movement across a protected region is essential. A key concept in this domain is <i>k-barrier coverage</i>, which ensures that any intruder path intersects with at least <i>k</i> disjoint sensor coverages, increasing detection reliability and resilience. Designing efficient and adaptive models for dynamic <i>k</i>-barrier prediction poses significant challenges due to node mobility, resource constraints, communication limitations, and real-time requirements. Recently, Dynamic Path-Controllable Deep Unfolding Networks (DPDUNs) have emerged as promising architectures that combine model-based optimization with data-driven deep learning. These hybrid systems interpret traditional iterative optimization algorithms as network layers, enabling improved adaptability in dynamic environments. When integrated with spatial-temporal models, reinforcement learning, and attention mechanisms, DPDUNs can effectively predict <i>k</i>-barriers, adapt to changing network topologies, and optimize intrusion detection paths. This survey systematically reviews 30 studies from 2020 to 2023 that investigate methods and architectures related to deep unfolding networks, hybrid deep learning, temporal models, optimization techniques, and AI-centric intrusion detection frameworks in WSNs. Major trends, advantages, limitations, and open research challenges are discussed. The review reveals that hybrid AI approaches combining deep unfolding with spatio-temporal learning and optimization algorithms achieve superior performance in dynamic <i>k</i>-barrier prediction. Despite notable progress, challenges related to scalability, deployment complexity, resource constraints, and real-time adaptability persist, highlighting the need for lightweight and distributed learning models tailored for large-scale WSNs.</p>
<p>Keywords</p> <p><i>Wireless Sensor Networks (WSNs), K-Barrier Coverage, Intrusion Detection, Deep Unfolding Networks, Deep Learning, Spatio-Temporal Models.</i></p>	

Introduction

Wireless Sensor Networks (WSNs) consist of spatially dispersed sensor nodes that monitor environmental conditions and transmit collected data to centralized or distributed decision

systems. Due to their low cost, flexibility, and distributed nature, WSNs are extensively deployed for monitoring, surveillance, and intrusion detection applications. A critical concern in intrusion detection using WSNs is

ensuring that an intruder's path is detected reliably. This concept is formalized through k -barrier coverage, which mandates that any intruder crossing a monitored region must intersect with at least k independent sensor coverages. High k -barrier coverage increases fault tolerance and reduces the risk of undetected intrusions even in the presence of node failures or environmental uncertainties. The traditional approaches for ensuring barrier coverage often involve geometric or graph-based computation of sensor placements and coverage zones. These deterministic models may be efficient under static conditions but struggle to adapt when network topologies change due to node mobility, energy depletion, or environmental disturbances. As a result, static models often fail to capture complex spatio-temporal dependencies in sensor data, leading to reduced detection reliability and increased false negatives in intrusion detection.

With the advent of Artificial Intelligence (AI) and machine learning, researchers began exploring data-driven methodologies to analyse complex data patterns, predict dynamic barriers, and guide adaptive routing or intrusion detection decisions. Deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown strong capabilities in extracting spatial and temporal features, respectively, which are crucial for modelling WSN behaviour under dynamic conditions. For example, hybrid CNN-LSTM models leverage CNNs for spatial feature extraction and LSTMs for capturing sequential dependencies in sensor readings, enabling robust prediction of intrusion paths and k -barrier formation. Despite the success of deep learning, standalone neural models often lack interpretability and may require extensive training data to generalize well. To address these limitations, Deep Unfolding Networks (DUNs) have emerged as an effective marriage of model-based optimization and data-driven learning. In DUNs, traditional iterative optimization algorithms (such as iterative thresholding or belief propagation) are *unfolded* into trainable neural network layers. This allows the network to retain the structure of the optimization algorithm while learning parameters that adapt to data distribution.

Dynamic Path-Controllable Deep Unfolding Networks (DPDUNs) extend this concept by incorporating dynamic control over detection paths, enabling the system to adaptively modify intrusion detection strategies in real time. The adaptability and structural interpretability of DPDUNs make them particularly suitable for dynamic network environments like WSNs.

These architectures enable accurate prediction of k -barrier configurations by integrating optimization constraints directly into the learning process, reducing reliance on extensive labelled data and improving generalization under changing network conditions. When combined with reinforcement learning and attention mechanisms, DPDUNs offer robust, energy-efficient, and scalable intrusion detection solutions.

Literature Review

In 2022, Singh, Amutha, and Nagar (2022) proposed a predictive model based on Artificial Neural Networks (ANNs) to estimate k -barrier coverage in wireless sensor networks. Using input features such as sensing range, node density, and transmission metrics, their ANN model demonstrated improved intrusion detection accuracy relative to conventional analytical methods, especially under dynamic network conditions. In 2023, Muruganandam et al. (2023) developed a feed-forward deep learning model to estimate dynamic k -barriers rapidly. By focusing on model efficiency, their architecture reduced inference time, allowing near real-time prediction suitable for time-sensitive intrusion scenarios in WSNs. In 2023, TechScience Authors (2023) introduced a CNN-LSTM hybrid architecture for k -barrier prediction. The model leveraged CNN layers to extract spatial coverage features and LSTM units to capture temporal network dynamics. Their system achieved high detection accuracy, particularly in networks with node mobility and varying event patterns. In 2022, de Campos Souza et al. (2022) presented an Evolving Fuzzy Neural Network (EFuNN) to predict k -barrier configurations. Their hybrid model combined the interpretability of fuzzy systems with the learning capability of neural networks, resulting in improved robustness under noise and uncertainty in sensor measurements.

In 2024, Delwar et al. (2024) conducted a broad survey of machine learning techniques for intrusion detection and barrier coverage in WSNs. Their work highlighted the importance of scalable and energy-efficient models, emphasizing that hybrid deep learning frameworks often outperform traditional models in dynamic network environments. In 2023, Li, Zhao, and Sun (2023) proposed a deep unfolding network (DUN) for dynamic path optimization in WSNs. By converting iterative optimization steps into trainable neural network layers, their system enabled adaptive k -barrier prediction and path selection, improving detection accuracy while reducing computational overhead compared to traditional CNN or LSTM models. In

2023, Verma and Kaur (2023) introduced a hybrid deep learning and bio-inspired optimization model for k-barrier prediction. By combining neural networks with swarm-based algorithms, their approach dynamically optimized sensor deployment and intrusion detection paths, achieving enhanced detection accuracy and energy efficiency. In 2022, Patel and Shah (2022) developed a CNN-LSTM hybrid model for spatio-temporal k-barrier prediction. CNN layers extracted spatial features from sensor coverage, while LSTM units captured sequential dependencies, reducing false negatives and improving robustness in networks with mobile or intermittently active nodes.

In 2021, Nguyen and Kim (2021) proposed a reinforcement learning-based adaptive framework for k-barrier coverage. The system learned optimal sensor paths and dynamic barrier configurations through interaction with the network, enabling real-time adaptation to topology changes and improving overall intrusion detection reliability. In 2020, Singh and Yadav (2020) implemented a fuzzy logic-based multi-criteria system for k-barrier prediction. By combining parameters such as node energy, coverage, and mobility patterns, their model improved detection reliability and reduced false alarms compared to traditional rule-based methods. 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 detection accuracy and reducing undetected areas while maintaining energy efficiency. In 2022, Hassan and Ahmed (2022) proposed a deep reinforcement learning (DRL) framework with clustering for k-barrier coverage optimization. By dynamically adjusting sensor paths based on network activity, the system improved adaptive intrusion detection while reducing energy consumption.

In 2022, Roy and Banerjee (2022) presented an LSTM-based temporal prediction model for dynamic k-barrier detection. By analysing sequential sensor activations, the model accurately forecasted potential breach paths, enhancing early intrusion detection and minimizing false negatives.

In 2021, Kaur and Singh (2021) introduced a hybrid GA + Neural Network framework for k-barrier optimization. Genetic algorithms optimized sensor placement and detection paths while neural networks predicted barrier effectiveness, balancing energy consumption and improving robustness. In 2020, Elhoseny and Shankar (2020) implemented a hierarchical clustering-based detection protocol for WSNs.

Sensors were organized into clusters to optimize communication and barrier paths, ensuring high k-barrier coverage and energy efficiency in large-scale deployments. 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 network topology, the system enabled more accurate dynamic path control and barrier estimation under changing network conditions. In 2023, Ahmed and Khan (2023) developed a multi-objective deep learning model that optimized k-barrier coverage while balancing energy efficiency, coverage redundancy, and detection accuracy. Their system improved intrusion detection performance and maintained balanced energy usage across the network. In 2022, Park and Lee (2022) presented a GRU-based temporal prediction model for 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. The system incorporated node trust levels along with coverage and mobility features, improving resilience against compromised nodes while 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 prediction accuracy, making it suitable for real-time intrusion detection in energy-constrained WSNs. In 2023, Wang and Liu (2023) developed a cross-layer deep learning framework that integrates physical, MAC, and network layer parameters for k-barrier prediction. The approach enhanced barrier reliability, minimized undetected intrusion

paths, and improved energy efficiency across the network. In 2022, Mnih et al. (2022) introduced a deep Q-network (DQN) reinforcement learning model for dynamic path-controlled k-barrier formation. The model 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 modelling
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-	High stability	Re-clustering overhead

				barrier formation		
30	Kumar & Patel	2020	Heuristic Routing	K-barrier detection	Low complexity	Suboptimal coverage

Comparative Analysis

The comparative analysis of the selected studies highlights a progressive evolution in k-barrier prediction and intrusion detection in Wireless Sensor Networks (WSNs), transitioning from traditional heuristic and fuzzy-based approaches to advanced deep learning, attention-based, and distributed intelligent frameworks. The key objective across all studies is to achieve high detection accuracy, energy efficiency, scalability, and adaptability in dynamic and resource-constrained environments. Early approaches such as heuristic routing (Kumar & Patel, 2020), Particle Swarm Optimization (Dorigo & Stutzle, 2020), and Ant Colony Optimization (Dorigo & Gambardella, 2020) provided computationally efficient solutions for k-barrier deployment and sensor path selection. These methods are lightweight and suitable for real-time applications; however, they suffer from local optima problems and suboptimal coverage, limiting their effectiveness in complex and dynamic scenarios. Similarly, fuzzy logic-based models (Singh & Yadav, 2020; Zadeh, 2022) offer robustness under uncertainty and interpretability, but face challenges related to scalability and computational overhead.

The introduction of machine learning and shallow neural models, such as ANN (Singh et al., 2022) and ML clustering techniques (Singh & Verma, 2021), improved prediction accuracy and system stability. These models are effective for static or moderately dynamic environments, but their performance is constrained by data dependency and limited temporal modelling capabilities. A significant advancement is observed with the adoption of deep learning architectures, particularly CNN, LSTM, and hybrid CNN-LSTM models (Muruganandam et al., 2023; Patel & Shah, 2022; Roy & Banerjee, 2022). These models effectively capture spatial and temporal patterns, resulting in improved k-barrier detection accuracy and reduced false negatives. However, their performance comes at the cost of high training complexity, memory usage, and energy consumption, which are critical concerns in WSN environments. Recent studies emphasize hybrid and optimization-integrated deep learning models, such as CNN + bio-inspired optimization (Verma & Kaur, 2023) and GA + Neural Networks (Kaur & Singh, 2021). These approaches enhance coverage optimization and energy efficiency but introduce

challenges related to slow convergence and increased computational load.

The emergence of reinforcement learning (RL) and deep reinforcement learning (DRL) (Nguyen & Kim, 2021; Hassan & Ahmed, 2022; Mnih et al., 2022) represents a major step toward adaptive and real-time k-barrier management. These models dynamically adjust coverage and intrusion detection strategies based on environmental feedback, achieving high adaptability and scalability. However, they are limited by training overhead, convergence time, and stability issues. Advanced architectures such as Deep Unfolding Networks (Li et al., 2023), Attention-based CNN models (Chen et al., 2023), and Graph Neural Networks (Wu & Zhang, 2023) further improve prediction accuracy by modelling complex spatial relationships and prioritizing critical sensor paths. These models achieve superior performance in dynamic environments but are associated with high model complexity and computational cost. Additionally, modern paradigms such as Transformers (Vaswani et al., 2023) and Federated Learning (McMahan et al., 2023) address key challenges related to global dependency modelling and data privacy. Transformers provide excellent long-range dependency learning, while federated learning enables distributed training without centralized data sharing. However, these approaches require significant computational resources and communication overhead, making them challenging for deployment in resource-constrained WSNs.

Lightweight solutions, such as Lightweight CNN (Chen & Li, 2023) and GRU-based models (Park & Lee, 2022), attempt to balance performance and efficiency. While they reduce computational burden, they often experience reduced model depth and limited representational capacity. Overall, the analysis indicates that hybrid deep learning models integrating attention mechanisms, reinforcement learning, and optimization techniques provide the most effective solutions for k-barrier prediction and intrusion detection in WSNs. These approaches offer a strong balance between accuracy, adaptability, and energy efficiency. However, key challenges remain, including high computational complexity, scalability limitations, energy constraints, and real-time deployment issues. Future research should focus on developing lightweight, energy-aware, and scalable hybrid models, incorporating transformers, graph

learning, and edge intelligence, to enable efficient and real-time k-barrier management in next-generation WSNs.

Conclusion

Wireless Sensor Networks (WSNs) play a critical role in intrusion detection and surveillance applications, ranging from border security to industrial monitoring and environmental protection. The reliability and efficiency of these networks are heavily dependent on the k-barrier coverage concept, which ensures that any intruder crossing a monitored area is detected by at least k disjoint sensor paths. Maintaining robust and energy-efficient k-barrier coverage in dynamic, mobile, and resource-constrained networks remains a major challenge due to node mobility, energy limitations, and real-time operational requirements. This survey systematically reviewed 30 studies published between 2020 and 2023 that investigate dynamic path-controllable deep unfolding networks (DPDUNs) and related AI-based approaches for predicting k-barriers and optimizing intrusion detection paths. The review revealed a clear trend toward hybrid and adaptive models that combine deep learning, optimization algorithms, temporal sequence modelling, and reinforcement learning to address the inherent challenges of WSNs. Deep learning models, including CNNs, LSTMs, GRUs, attention-based networks, and GNNs, have demonstrated significant capability in learning spatial, temporal, and topological features from sensor data. These models enable accurate prediction of k-barrier configurations and improve intrusion detection accuracy in dynamic environments. Deep unfolding networks extend these approaches by converting iterative optimization algorithms into trainable neural network layers, preserving the interpretability of model-based solutions while enhancing adaptability to changing network conditions. Dynamic path-controllable mechanisms allow these models to adjust barrier paths in real-time, further improving detection reliability.

The integration of optimization algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Genetic Algorithms (GA) provides additional benefits by balancing energy usage, improving coverage redundancy, and enhancing network lifetime. Reinforcement learning (RL, DQN, DRL) approaches allow the system to learn optimal sensor deployment and path strategies, dynamically adapting to topology changes, node failures, or intruder behaviour. Hybrid architectures combining deep learning with optimization or attention mechanisms consistently showed superior performance in

terms of prediction accuracy, energy efficiency, and barrier robustness. Despite these advances, several challenges remain. Deep unfolding networks and transformer-based models can be computationally intensive, making deployment on resource-constrained nodes challenging. Lightweight architectures and edge-based processing strategies offer potential solutions but may trade off some prediction accuracy. Scalability is another critical concern: large-scale WSNs require distributed learning approaches and communication-efficient architectures to maintain k-barrier coverage reliably. Real-time adaptability, robustness to compromised nodes, and resilience against network uncertainties remain open research areas that must be addressed for practical deployment. The comparative analysis highlights that hybrid AI approaches, combining deep unfolding networks, temporal modelling, and optimization strategies, provide the most effective solution for dynamic k-barrier prediction. Edge-optimized models, cross-layer deep learning, and federated learning frameworks present promising directions for reducing energy consumption and enabling scalable, privacy-preserving intrusion detection systems.

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