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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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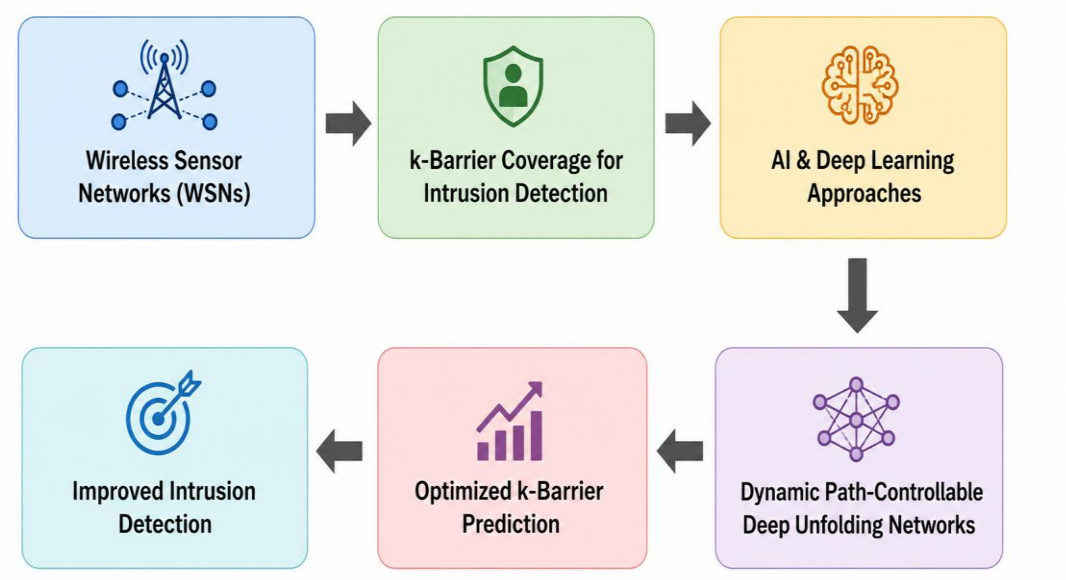
Abstract

Wireless Sensor Networks (WSNs) play a vital role in surveillance and intrusion detection applications, where reliable monitoring of unauthorized movement is essential. An important concept in this field is k barrier coverage, which ensures that every intrusion path intersects at least k sensor barriers, thereby improving detection reliability and fault tolerance. However, dynamic k barrier prediction remains challenging because of node mobility, limited resources, communication constraints, and real time operational demands. Recent advances in Dynamic Path Controllable Deep Unfolding Networks (DPDUNs) have provided promising solutions by integrating optimization based methods with deep learning techniques. These hybrid architectures transform iterative optimization processes into neural network layers, enabling adaptive learning in dynamic WSN environments. Combined with spatial temporal models, reinforcement learning, and attention mechanisms, DPDUNs improve barrier prediction accuracy and optimize intrusion detection paths under changing network conditions. This survey reviews 30 studies published between 2020 and 2023 on deep unfolding networks, hybrid AI models, temporal learning, optimization strategies, and AI driven intrusion detection frameworks for WSNs. The review highlights major trends, strengths, limitations, and research gaps. Although hybrid AI approaches show superior performance, challenges such as scalability, deployment complexity, energy efficiency, and real time adaptability still require further research.

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-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 clear evolution in k-barrier prediction and intrusion detection techniques in Wireless Sensor Networks (WSNs), moving from traditional heuristic and fuzzy logic methods toward advanced deep learning and intelligent distributed frameworks. Early approaches, including heuristic routing, Particle Swarm Optimization, and Ant Colony Optimization, focused on efficient sensor deployment and path selection with low computational overhead. These methods were suitable for real-time applications because of their lightweight nature and fast execution. However, they often suffered from local optimum problems, reduced adaptability, and limited coverage efficiency in highly dynamic environments. Similarly, fuzzy logic-based approaches improved robustness under uncertain conditions and provided interpretable decision-making mechanisms, but scalability and computational overhead restricted their performance in large-scale WSN deployments.

The integration of machine learning techniques introduced significant improvements in prediction accuracy and network stability. Artificial Neural Networks (ANNs) and clustering-based machine learning models enabled better intrusion detection in static and moderately dynamic environments. Nevertheless, these models were highly dependent on training data and lacked efficient temporal learning capabilities. Deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid CNN-LSTM models marked a major advancement by effectively capturing spatial and temporal patterns in sensor data. These approaches achieved higher k-barrier detection accuracy and lower false negative rates. Despite these benefits, deep learning methods introduced challenges related to high memory consumption, energy usage, and computational complexity, which are critical limitations in resource-constrained WSN environments.

Recent studies increasingly emphasize hybrid and optimization-integrated deep learning models. Techniques combining CNNs with bio-inspired optimization algorithms or Genetic Algorithms with Neural Networks have improved energy efficiency and coverage optimization. Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) further enhanced adaptability by enabling dynamic coverage adjustment based on environmental feedback. Advanced architectures such as Deep Unfolding Networks, Attention-based CNNs, and Graph Neural Networks significantly improved the modelling of spatial relationships and critical sensor paths. Similarly, Transformer architectures and Federated Learning frameworks addressed long-range dependency learning and data privacy concerns, supporting distributed and intelligent WSN management.

Lightweight architectures, including Lightweight CNNs and GRU-based models, attempt to reduce computational burden while maintaining acceptable prediction performance. However, their reduced complexity often limits representational power and learning depth.

Overall, hybrid deep learning frameworks integrating attention mechanisms, reinforcement learning, optimization techniques, graph learning, and edge intelligence provide the most effective solutions for dynamic k-barrier prediction and intrusion detection. Although these approaches achieve strong accuracy, adaptability, and energy efficiency, challenges related to scalability, computational overhead, and real-time deployment still remain significant areas for future research.

Conclusion

Wireless Sensor Networks (WSNs) are widely used in intrusion detection and surveillance applications such as border monitoring, industrial security, and environmental protection. Their effectiveness largely depends on **k-barrier coverage**, which ensures that an intruder crossing a monitored region is detected by at least *k* disjoint sensing paths. However, maintaining reliable and energy-efficient k-barrier coverage is challenging in dynamic WSNs because of node mobility, limited battery power, topology variations, and strict real-time requirements. This survey reviewed 30 studies published between 2020 and 2023 focusing on dynamic path-controllable deep unfolding networks (DPDUNs) and related AI-driven methods for predicting k-barriers and improving intrusion detection.

The review identified a strong shift toward adaptive and hybrid AI models integrating deep learning, optimization, and temporal sequence modelling. Architectures such as CNNs, LSTMs, GRUs, Graph Neural Networks, and attention-based models effectively learn spatial, temporal, and topological patterns from sensor data, enabling accurate prediction of barrier configurations. Deep unfolding networks further enhance these methods by transforming iterative optimization algorithms into trainable neural layers, combining interpretability with adaptability. Dynamic path-controllable mechanisms allow routing paths to be adjusted in real time, improving barrier stability and detection reliability.

Optimization techniques including PSO, ACO, and Genetic Algorithms improve energy balancing, coverage redundancy, and network lifetime, while reinforcement learning supports adaptive path selection under changing conditions. Although hybrid models deliver superior performance, challenges remain in computational complexity, scalability, and real-time deployment on resource-constrained nodes. Future research should prioritize lightweight edge-based architectures, federated learning, and distributed intelligence for scalable, energy-aware intrusion detection systems.

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