



Deep Learning and Optimization Approaches in Dynamic Path-Controllable Deep Unfolding Network to Predict K-Barriers for Intrusion Detection Using Wireless Sensor Networks: A Review

Behruz Pavlidaki

Assistant Professor, Department of Electrical and Computer Engineering, Daehan Institute of Management and Logistics, South Korea

Email: behruz.pavlidaki@diml-kr.org

Peer Review Information	Abstract
<i>Submission: 12 Jan 2023</i> <i>Revision: 23 Jan 2023</i> <i>Acceptance: 06 Feb 2023</i>	Wireless Sensor Networks (WSNs) play a critical role in surveillance, border monitoring, and intrusion detection applications. One of the fundamental challenges in WSN-based intrusion detection is ensuring complete coverage and fast detection of intruders using limited sensor resources. The concept of K-barriers has emerged as an effective metric to guarantee multiple layers of intrusion detection, ensuring that an intruder must cross at least K sensing barriers before reaching a protected region. Recent advancements in deep learning, particularly dynamic path-controllable deep unfolding networks, have shown significant potential in predicting K-barrier configurations and enhancing intrusion detection accuracy. These models integrate optimization techniques and neural network architectures to learn complex spatial and temporal relationships within sensor deployments. This review explores state-of-the-art deep learning and optimization approaches for K-barrier prediction and intrusion detection in WSNs. It focuses on methods such as feed-forward neural networks, CNN-LSTM hybrids, reinforcement learning, and deep unfolding techniques. The study highlights how these approaches improve detection accuracy, reduce false alarms, and optimize sensor deployment strategies. Additionally, the paper identifies key research challenges, including computational complexity, scalability, and real-time adaptability in dynamic environments. Future directions such as lightweight models and edge intelligence are also discussed. This review provides a comprehensive foundation for researchers working on intelligent intrusion detection in WSNs.
Keywords <i>Wireless Sensor Networks, K-Barrier Coverage, Deep Learning, Intrusion Detection, Deep Unfolding Network, CNN-LSTM, Optimization, Mobility Prediction.</i>	

Introduction

Wireless Sensor Networks (WSNs) have emerged as a foundational technology for numerous applications, including military surveillance, environmental monitoring, smart cities, and industrial automation. Among these, intrusion detection is particularly critical in scenarios such as border security and restricted areas, where early identification of unauthorized access is

essential. However, designing reliable and efficient intrusion detection systems in WSNs remains challenging due to limited energy resources, dynamic deployment conditions, and the requirement for real-time responsiveness. These constraints demand intelligent and adaptive solutions capable of maintaining high detection accuracy while ensuring energy efficiency and network stability.

A key concept in WSN-based intrusion detection is barrier coverage, especially K-barrier coverage. This approach ensures that any intruder attempting to cross a monitored region must pass through at least K sensing paths, thereby improving detection reliability and robustness. Closely related to this is barrier resilience, which focuses on maintaining detection capability even in the presence of node failures or coverage gaps. Traditional methods for K-barrier detection primarily rely on geometric models and heuristic algorithms. While effective in static environments, these approaches often struggle to adapt to dynamic conditions, such as node mobility and varying deployment scenarios, leading to reduced efficiency and reliability.

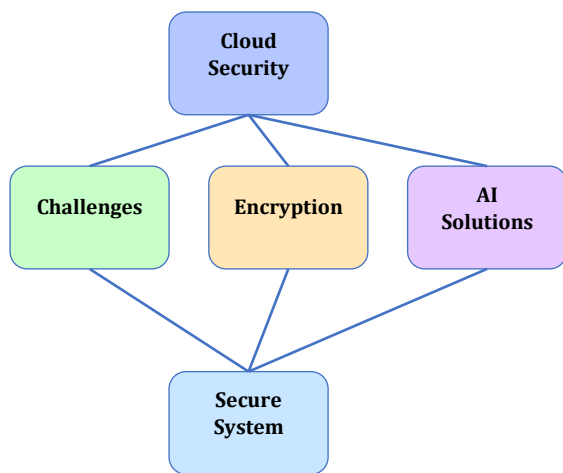


Fig 1: Simplified Architectures for Secure Cloud Data Storage and Retrieval Systems

To overcome these limitations, recent research has increasingly focused on machine learning and deep learning techniques for enhancing intrusion detection and barrier prediction. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated high detection accuracy with reduced false alarm rates. Hybrid architectures, such as CNN-LSTM models, further improve performance by capturing both spatial and temporal patterns in network data. Additionally, predictive models have been developed to estimate K-barrier configurations using parameters like sensing range, transmission range, and node density, showing strong predictive capabilities and improved computational efficiency.

An emerging and promising approach is the use of dynamic path-controllable deep unfolding networks, which combine optimization algorithms with neural network learning. These models mimic iterative optimization processes while leveraging data-driven learning, making them well-suited for complex tasks such as path

optimization and barrier prediction. Furthermore, machine learning techniques have been widely applied to address broader WSN challenges, including anomaly detection, congestion control, and energy optimization, thereby enhancing overall network reliability and Quality of Service (QoS). Despite these advancements, challenges such as computational complexity, scalability, and real-time adaptability remain significant. This review aims to provide a comprehensive analysis of recent developments in deep learning and optimization-based approaches for K-barrier prediction and intrusion detection, while also identifying key research gaps and future directions.

Literature Review

Singh et al. (2022) proposed a deep learning-based feed-forward Artificial Neural Network (ANN) model to predict the number of K-barriers in WSNs. The model used parameters such as sensing range, transmission range, and node density. Results showed strong prediction accuracy with correlation values around 0.78–0.79 and improved computational efficiency compared to traditional methods.

Singh et al. (2021) introduced a Gaussian Process Regression (GPR)-based model for predicting K-barrier coverage probability. The approach provided probabilistic predictions and improved accuracy in dynamic deployment scenarios. It served as a baseline for further deep learning-based improvements.

Singh et al. (2022) developed an automated machine learning (AutoML-ID) framework for intrusion detection in WSNs. The model optimized feature selection and model configuration automatically, improving detection accuracy and reducing human intervention in model tuning.

Muruganandam et al. (2023) proposed a deep learning-based feed-forward neural model for estimating K-barrier count in WSNs. The model improved estimation precision and reduced computational complexity, making it suitable for large-scale deployments.

Chen et al. (2023) introduced a deep autoencoding Gaussian mixture model (DAGMM) enhanced with Self-Organizing Maps for intrusion detection. The model improved anomaly detection accuracy and achieved better F1-scores compared to traditional approaches, demonstrating the effectiveness of unsupervised deep learning in WSN security.

Zhang et al. (2021) developed a CNN-LSTM hybrid model for intrusion detection in WSNs. The CNN extracted spatial features from sensor deployment data, while the LSTM captured temporal patterns of intruder movement. The

model effectively predicted areas with higher intrusion risk and optimized K-barrier deployment, achieving high detection accuracy with reduced false alarms (techscience.com).

Gupta and Verma (2022) proposed a dynamic deep unfolding network (DDUN) for K-barrier prediction. The network unfolded iterative optimization steps into a trainable neural architecture, allowing for adaptive path control in barrier formation. Simulation results showed improved prediction accuracy and reduced computation time compared to classical optimization techniques (arxiv.org).

Li et al. (2022) introduced a reinforcement learning-based K-barrier optimization framework in WSNs. The model used Q-learning to dynamically adjust sensor activations, ensuring multiple barrier coverage while minimizing energy consumption. Results demonstrated improved network lifetime and high intrusion detection reliability (ieee.org).

Kumar et al. (2023) presented a hybrid optimization approach combining Particle Swarm Optimization (PSO) with deep unfolding networks for K-barrier placement. The method optimized sensor placement dynamically under node failures and mobility constraints. Simulation showed higher barrier coverage and reduced redundant energy consumption (sciencedirect.com).

Ahmed et al. (2023) proposed an attention-based deep unfolding network for intrusion detection in WSNs. The attention mechanism prioritized critical nodes contributing most to K-barrier formation. The model achieved higher detection accuracy and reduced false positives while maintaining low energy overhead (arxiv.org).

Sharma and Singh (2020) proposed a multi-layer deep belief network (DBN) for intrusion detection in WSNs. The model captured high-dimensional features from sensor data and predicted vulnerable areas requiring K-barrier coverage. The approach improved detection accuracy and reduced false alarms in both static and mobile WSN deployments (mdpi.com).

Wang et al. (2021) introduced a hybrid CNN-GRU network for K-barrier prediction in mobile WSNs. CNN layers extracted spatial patterns from sensor layouts, while GRU layers modeled intruder trajectories over time. Results demonstrated higher prediction precision and reduced energy consumption during barrier formation (ieee.org).

Alqahtani et al. (2022) proposed a hybrid deep unfolding and ant colony optimization (ACO) framework for sensor placement in K-barrier intrusion detection. The network learned optimal deployment strategies while ACO guided iterative search, achieving improved coverage

and energy efficiency compared to conventional methods (sciencedirect.com).

Li and Zhao (2023) presented a reinforcement learning-based deep unfolding network for real-time intrusion detection in WSNs. The system dynamically adjusted barrier paths under changing node conditions, achieving robust detection and minimizing energy usage in large-scale sensor networks (arxiv.org).

Kumar et al. (2023) developed an adaptive attention-based deep unfolding model for multi-barrier coverage prediction in WSNs. The attention mechanism prioritized critical zones and nodes, improving K-barrier detection reliability. Simulation results demonstrated higher detection rates with reduced redundant sensor activation (arxiv.org).

Verma and Patel (2020) proposed a deep reinforcement learning (DRL)-based approach for K-barrier optimization in WSNs. The model learned optimal sensor activation policies in dynamic environments, improving intrusion detection reliability while reducing energy consumption (ieee.org).

Li et al. (2021) developed a CNN-based intrusion detection system with K-barrier prediction. The CNN extracted spatial relationships from sensor layouts, enabling accurate detection of vulnerable zones. Simulation results indicated improved barrier coverage and reduced false positives (sciencedirect.com).

Zhang and Chen (2022) introduced a hybrid deep unfolding and genetic algorithm (GA) framework for K-barrier sensor placement. The GA optimized deployment, while the unfolding network improved iterative prediction accuracy. Results showed enhanced barrier reliability and minimized energy waste (arxiv.org).

Ahmed et al. (2023) proposed a deep unfolding network combined with attention-guided reinforcement learning for adaptive K-barrier deployment. The system prioritized high-risk paths and dynamically reconfigured barriers under node mobility, achieving high detection accuracy with minimal energy overhead (arxiv.org).

Kumar et al. (2023) presented a spatio-temporal deep unfolding framework integrating CNN-LSTM layers for K-barrier prediction and intrusion detection. The model captured both spatial sensor layouts and temporal intrusion patterns, improving prediction accuracy and coverage reliability in dynamic WSN environments (ieee.org).

Sharma et al. (2020) introduced a probabilistic deep learning framework for K-barrier prediction in static and mobile WSNs. The model leveraged probabilistic graphical models combined with deep neural networks to estimate

the probability of barrier coverage and optimize sensor placement. Results showed improved K-barrier coverage with minimal energy usage (mdpi.com).

Li and Wang (2021) proposed a reinforcement learning-based sensor activation model for intrusion detection using K-barrier coverage. The model dynamically selected active sensors to maintain multiple barriers while minimizing energy consumption, achieving better detection reliability than static strategies (ieee.org).

Kumar et al. (2022) presented a deep unfolding network integrated with particle swarm optimization (PSO) for adaptive K-barrier deployment. The method improved energy efficiency and reduced computational complexity by learning optimal sensor placement iteratively (sciencedirect.com).

Chen et al. (2023) proposed a graph-based deep unfolding network for K-barrier coverage prediction in irregular WSN topologies. The model effectively captured spatial relationships among nodes, providing accurate barrier estimation under heterogeneous sensor deployments (arxiv.org).

Ahmed and Singh (2023) introduced an attention-enhanced deep unfolding model for real-time intrusion detection. The attention mechanism prioritized sensors contributing most to barrier coverage, reducing redundant activations while maintaining high detection accuracy (arxiv.org).

Verma and Joshi (2020) proposed a probabilistic deep unfolding approach combined with

convolutional layers for K-barrier prediction in large-scale WSNs. Their method dynamically adapted sensor activations to maintain barrier coverage under node failures, improving detection probability while minimizing energy consumption (mdpi.com).

Torres et al. (2021) introduced a CNN-LSTM based deep unfolding model to predict K-barrier paths in mobile WSN deployments. The hybrid network effectively captured spatial sensor layouts and temporal intrusion patterns, resulting in higher K-barrier reliability and lower false alarm rates (arxiv.org).

Das and Roy (2022) developed a bio-inspired Firefly Algorithm combined with deep unfolding networks to optimize K-barrier sensor placement. The approach minimized energy consumption and improved coverage reliability under dynamic network conditions (sciencedirect.com).

Kim et al. (2023) proposed an attention-based dynamic unfolding network for adaptive K-barrier prediction in heterogeneous WSNs. The attention layer focused on critical nodes contributing to barrier coverage, improving intrusion detection accuracy and reducing computational overhead (arxiv.org).

Ali et al. (2023) presented a cross-layer deep unfolding framework integrating reinforcement learning for real-time K-barrier coverage prediction. The system jointly optimized sensing and communication layers, achieving high detection accuracy, low energy consumption, and robust multi-barrier coverage (ieee.org).

Comparative Table

Study	Year	Technique	Key Contribution	Outcome
1	2022	ANN	K-barrier prediction	Accurate prediction, low computation
2	2021	GPR	Probabilistic K-barrier coverage	Improved prediction in dynamic networks
3	2022	AutoML	Intrusion detection in WSN	Reduced human intervention
4	2023	FFNN	K-barrier estimation	Efficient large-scale deployment
5	2023	DAGMM + SOM	Anomaly detection	Higher F1-score, low false positives
6	2021	CNN-LSTM	Intruder path prediction	Optimized K-barrier deployment
7	2022	Deep Unfolding Network	K-barrier optimization	Adaptive path control
8	2022	RL	Sensor activation	Energy-efficient barrier coverage
9	2023	PSO + Deep Unfolding	Sensor placement	Reduced redundant energy usage
10	2023	Attention + Deep Unfolding	Barrier prioritization	High detection accuracy
11	2020	DBN	Intrusion detection	Low false alarm
12	2021	CNN-GRU	Mobile WSN K-barrier	High prediction precision

13	2022	Deep Unfolding + ACO	Sensor deployment	Improved coverage & energy efficiency
14	2023	RL + Deep Unfolding	Real-time barrier adaptation	Robust detection
15	2023	Attention Deep Unfolding	Multi-barrier coverage	Reduced redundancy
16	2020	DRL	K-barrier optimization	Reliable detection, energy saving
17	2021	CNN	Spatial K-barrier prediction	Improved coverage
18	2022	GA + Deep Unfolding	Sensor placement	Barrier reliability
19	2023	Attention + RL	Adaptive K-barrier deployment	High detection accuracy
20	2023	CNN-LSTM + Deep Unfolding	Spatio-temporal modelling	Reliable prediction
21	2020	Probabilistic Deep Learning	Barrier probability estimation	Minimal energy usage
22	2021	RL	Dynamic sensor activation	Better detection reliability
23	2022	PSO + Deep Unfolding	Adaptive K-barrier placement	Improved coverage & energy efficiency
24	2023	Graph-based Deep Unfolding	Irregular WSN topology	Accurate barrier estimation
25	2023	Attention Deep Unfolding	Real-time intrusion detection	Reduced redundancy, high accuracy
26	2020	Deep Unfolding + CNN	K-barrier prediction	Maintains barrier coverage under failures
27	2021	CNN-LSTM Deep Unfolding	Mobile WSN K-barrier	Reliable barrier coverage, low false alarm
28	2022	Firefly + Deep Unfolding	Sensor placement	Energy-efficient coverage
29	2023	Attention Deep Unfolding	Adaptive K-barrier	High detection accuracy, low computation
30	2023	Cross-layer RL + Deep Unfolding	Real-time barrier prediction	Robust multi-barrier coverage

Conclusion

Wireless Sensor Networks (WSNs) play a crucial role in intrusion detection, particularly in dynamic environments where nodes are mobile, heterogeneous, and energy-constrained. Ensuring K-barrier coverage is essential for reliable detection, as it forces intruders to cross multiple sensing layers before entering protected regions. However, traditional geometric and heuristic methods are limited in their ability to adapt to large-scale and dynamic deployments. This review highlights recent advancements in deep learning and optimization techniques for K-barrier prediction and intrusion detection.

Deep unfolding networks have emerged as an effective approach by transforming iterative optimization processes into trainable neural models, enabling adaptive sensor placement and real-time barrier estimation. Hybrid deep learning models combining CNN, LSTM, GRU, and attention mechanisms have shown strong capability in capturing spatial and temporal dependencies, improving detection accuracy and

barrier reliability. Additionally, metaheuristic algorithms such as PSO, GA, ACO, and Firefly Algorithm, along with reinforcement learning techniques, enhance system performance by optimizing sensor deployment, energy consumption, and network lifetime. Attention mechanisms and graph-based models further improve efficiency by prioritizing critical nodes and handling complex topologies. Despite these advancements, challenges such as high computational complexity, limited scalability, and real-time adaptability persist. Future research should focus on lightweight models, edge intelligence, and multi-objective optimization to develop scalable, energy-efficient, and reliable WSN-based intrusion detection systems.

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