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**International Journal on Advanced Computer Engineering and Communication Technology**

ISSN: 2278-5140

Volume 14 Issue 02, 2025

# 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

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**Peer Review Information**

*Submission: 28 Oct 2025*

*Revision: 20 Nov 2025*

*Acceptance: 08 Dec 2025*

**Keywords**

*Wireless Sensor Networks, K-Barrier Coverage, Deep Learning, Intrusion Detection, Deep Unfolding Network, CNN-LSTM, Optimization, Mobility Prediction.*

**Abstract**

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.

## Introduction

Wireless Sensor Networks (WSNs) have become a fundamental technology for a wide range of applications, including military surveillance, environmental monitoring, smart cities, and industrial automation. Among these applications, intrusion detection is one of the most critical, especially in border security and restricted zones where early detection of unauthorized entities is essential. However, ensuring reliable and efficient intrusion detection in WSNs remains a significant challenge due to limited energy resources, dynamic deployment environments, and the need for real-time responsiveness.

One of the key concepts in WSN-based intrusion detection is barrier coverage, particularly K-barrier coverage. K-barrier coverage ensures that any intruder attempting to cross a monitored region must intersect at least K sensing paths, thereby increasing detection reliability. This concept is closely related to barrier resilience, where the objective is to maximize detection robustness even in the presence of node failures or coverage gaps.

Traditional approaches to K-barrier detection rely on geometric models and heuristic algorithms. However, these methods often struggle to adapt to dynamic environments where sensor nodes may be mobile or where deployment conditions change over time. As a result, there has been a growing interest in applying machine learning and deep learning techniques to enhance intrusion detection capabilities in WSNs.

Recent studies have demonstrated that deep learning models can significantly improve intrusion detection accuracy and efficiency. For example, CNN-based intrusion detection systems have achieved high accuracy (up to 97%) while maintaining low false alarm rates in WSN environments. Similarly, hybrid models combining CNN and LSTM have been effective in capturing both spatial and temporal patterns in network traffic, leading to improved detection performance.

A particularly promising direction is the use of deep learning for predicting K-barrier configurations. Singh et al. (2022) proposed a feed-forward neural network model to predict the number of K-barriers based on network parameters such as sensing range, transmission range, and node density. Their model demonstrated strong predictive performance with correlation coefficients around 0.78–0.79, highlighting the effectiveness of deep learning in solving this problem.

Furthermore, dynamic path-controllable deep unfolding networks represent an emerging class of models that integrate optimization algorithms with neural networks. These models mimic iterative optimization processes while leveraging the learning capability of neural networks, making them highly suitable for solving complex problems such as path optimization and barrier prediction in WSNs.

Machine learning techniques have also been widely applied to enhance WSN security, addressing challenges such as anomaly detection, congestion control, and energy optimization. These approaches improve network reliability and Quality of Service (QoS), which are essential for effective intrusion detection.

Despite these advancements, several challenges remain. The computational complexity of deep learning models can be a limiting factor in resource-constrained WSN environments. Additionally, scalability and real-time adaptability are critical issues that need to be addressed for practical deployment.

This review aims to provide a comprehensive analysis of deep learning and optimization approaches for K-barrier prediction and intrusion detection in WSNs. It focuses on recent developments (2020–2023), highlighting key methodologies, contributions, and research gaps.

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**

Intrusion detection in Wireless Sensor Networks (WSNs) is a critical challenge, particularly in dynamic environments where sensor nodes may be mobile, energy-constrained, or heterogeneous. Ensuring K-barrier coverage is vital for robust detection, as it guarantees that an intruder must intersect at least K sensing layers before entering the protected area. Traditional geometric and heuristic methods, while effective in static scenarios, fail to adapt to dynamic or large-scale deployments.

This review highlights the significant advancements in deep learning and optimization approaches for K-barrier prediction and intrusion detection between 2020 and 2023. Among these, deep unfolding networks have emerged as a powerful paradigm. By unfolding iterative optimization steps into trainable neural architectures, these networks achieve adaptive and efficient sensor placement, allowing for real-time barrier prediction. Hybrid models integrating CNN, LSTM, GRU, and attention mechanisms have demonstrated exceptional ability to capture spatial and temporal dependencies, enhancing both K-barrier reliability and intrusion detection accuracy.

Metaheuristic algorithms, such as Particle Swarm Optimization (PSO), Firefly Algorithm, Genetic Algorithms (GA), and Ant Colony Optimization (ACO), have been successfully combined with deep learning to optimize sensor deployment and minimize energy consumption. Reinforcement learning-based methods, including Q-learning and deep reinforcement learning (DRL), enable WSNs to adaptively select active sensors, maintain multi-barrier coverage, and extend network lifetime under dynamic conditions.

Attention mechanisms have further improved system performance by prioritizing critical nodes and paths, reducing redundant sensor activations, and lowering energy overhead while maintaining high detection accuracy. Graph-based deep unfolding networks provide solutions for irregular and heterogeneous topologies, ensuring reliable K-barrier estimation in complex deployments.

Despite these advances, several challenges remain. Computational complexity and memory overhead of deep learning models limit deployment on resource-constrained sensor nodes. Real-time adaptability, particularly in large-scale and mobile WSNs, remains an open research area. Additionally, joint optimization of energy, coverage, and latency requires further exploration, particularly in edge computing and cross-layer design.

Future research should focus on lightweight deep unfolding architectures, edge intelligence, and multi-objective optimization frameworks to enable scalable, real-time, and energy-efficient K-barrier deployment. Combining predictive mobility models with deep learning could further enhance barrier reliability in dynamic scenarios. Standardized benchmarking datasets and simulation environments are also needed to facilitate comparative evaluation across methodologies.

In conclusion, the integration of deep unfolding networks, attention mechanisms, reinforcement learning, and metaheuristic optimization represents a promising direction for predicting K-barriers and enhancing intrusion detection in WSNs. Continued research in this area is expected to produce highly adaptive, energy-efficient, and reliable WSNs capable of real-time multi-barrier intrusion detection in complex and dynamic environments.

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