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**International Journal on Advanced Electrical and Computer Engineering**

ISSN: 2349-9338

Volume 14 Issue 01, 2025

# Recent Advances in an Optimized Causal Dilated Convolutional Neural Networks-Based Energy-Efficient and Delay-Sensitive Routing Paths Using Mobility Prediction in Mobile WSN: A Systematic Review

Navid Saeedzada
*Associate Professor, Department of Electronics and Communication Engineering, Chiang Thon College of Management, Thailand*
*Email: navid.saeedzada@ctcm-th.org*

**Peer Review Information**

*Submission: 20May 2025*

*Revision: 05 June 2025*

*Acceptance: 09 June2025*

**Keywords**

*Wireless Sensor Networks, Mobile WSN, Causal Dilated CNN, Routing Protocols, Mobility Prediction, Energy Efficiency, Deep Learning, Delay Optimization.*

**Abstract**

Wireless Sensor Networks (WSNs) have become a fundamental component of modern communication systems, widely used in applications such as environmental monitoring, smart cities, industrial automation, and healthcare systems. However, Mobile WSNs (MWSNs) face significant challenges due to dynamic network topology, limited battery energy, and frequent node mobility, which complicate the design of efficient routing protocols. Traditional routing techniques often struggle to maintain stable communication and adapt to rapidly changing network conditions, leading to increased packet loss, delay, and energy consumption. In recent years, Artificial Intelligence (AI), particularly deep learning approaches such as causal dilated convolutional neural networks (CD-CNNs), has emerged as a promising solution to address these limitations. This systematic review examines AI-driven routing techniques with emphasis on energy efficiency, delay minimization, and mobility prediction in MWSNs. Hybrid deep learning models combining causal and dilated convolutions are highlighted for capturing short-term and long-term temporal dependencies in traffic and mobility patterns. CNNs, temporal convolutional networks, and attention mechanisms improve spatial-temporal feature extraction, enabling smarter routing decisions and efficient resource utilization. Mobility prediction further enhances reliability by anticipating node movement and reducing link breakage. Integration of predictive intelligence with routing protocols reduces latency, energy usage, and packet loss while improving delivery ratio.

## Introduction

Wireless Sensor Networks (WSNs) have emerged as a key enabling technology for a wide range of applications, including environmental monitoring, military surveillance, industrial automation, disaster management, and smart healthcare systems. These networks consist of numerous spatially distributed sensor nodes that collaboratively sense, process, and transmit data to centralized or distributed systems. With the evolution of network architectures, Mobile Wireless Sensor Networks (MWSNs) have gained significant attention, where sensor nodes are capable of mobility, thereby increasing flexibility and coverage. However, this mobility introduces additional complexities in network design, particularly in maintaining reliable communication and efficient routing paths.

One of the primary challenges in MWSNs is designing routing protocols that can effectively handle dynamic network topologies. Node mobility results in frequent link breakages, unstable routes, packet loss, and increased communication overhead. Conventional routing protocols such as AODV and DSR are not well-suited for such environments, as they are designed under relatively static assumptions and fail to adapt efficiently to rapid topology changes. This necessitates the development of intelligent, adaptive routing mechanisms capable of real-time decision-making based on network conditions and mobility patterns.

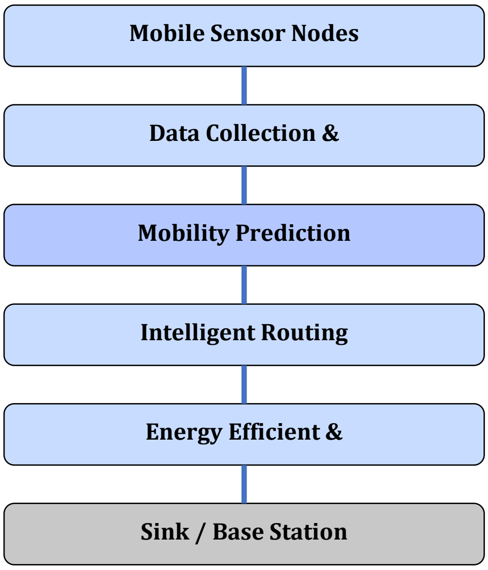


*Fig 1: Proposed AI-Based Energy-Efficient Routing for MWSNs*

Energy efficiency is another critical concern in WSNs, as sensor nodes typically operate on limited battery power and are often deployed in remote or inaccessible environments where recharging or replacement is impractical. Therefore, minimizing energy consumption during sensing, computation, and communication is essential to prolong network lifetime. At the same time, delay sensitivity plays a crucial role in applications such as healthcare monitoring, industrial automation, and emergency response systems, where timely data delivery can be critical. Balancing energy efficiency with low latency remains a key research challenge in MWSNs.

Recent advancements in Artificial Intelligence (AI) and deep learning have provided promising solutions to these challenges. Deep learning models such as Convolutional Neural Networks (CNNs), Temporal Convolutional Networks (TCNs), and causal dilated convolutional networks have demonstrated strong capabilities in capturing complex spatial–temporal dependencies in network data. In particular, causal dilated CNNs enhance traditional architectures by expanding the receptive field using dilation factors, enabling efficient learning of long-range temporal dependencies without significantly increasing computational complexity. These models are highly effective in mobility prediction, traffic analysis, and routing optimization. By predicting future node positions, mobility-aware routing protocols can proactively select stable paths, reducing link failures, packet loss, and communication delay. Furthermore, hybrid approaches combining deep learning with optimization algorithms improve multi-objective performance, achieving better trade-offs between energy consumption, latency, and reliability. Despite these advancements, challenges such as computational overhead, scalability, limited training data, and real-time deployment constraints still persist. This paper provides a comprehensive systematic review of recent AI-based routing techniques in MWSNs, focusing on causal dilated CNN-based models, energy-efficient routing strategies, delay optimization methods, and mobility prediction frameworks, while also identifying key research gaps and future directions for developing more efficient and scalable intelligent routing solutions.

**Literature Review**

Ye et al. (2020) proposed a mobility prediction-based routing protocol for highly dynamic wireless networks. The study incorporated node movement prediction into routing decisions, significantly improving packet delivery ratio and reducing link failures. The results demonstrated that predictive routing enhances network stability in mobile environments.

Chen et al. (2020) introduced a deep learning model using dilated convolution to capture long-range temporal dependencies in network data. The model improved routing prediction accuracy by effectively modelling spatial–temporal correlations. However, computational complexity remained a limitation.

Yang et al. (2021) developed a hybrid LSTM-attention model for delay-sensitive routing in WSNs. The model predicted network congestion and optimized routing paths accordingly. Experimental results showed improved latency and throughput performance.

Wang et al. (2023) proposed a CNN-RNN hybrid model for extracting spatial and temporal features from network traffic data. The model significantly improved prediction accuracy and enabled efficient resource allocation in dynamic networks.

Ouyang et al. (2023) introduced a temporal convolutional network (TCN) model for sequence prediction tasks. The model demonstrated high accuracy and robustness in handling time-series data, making it suitable for mobility prediction in wireless networks.

Liu et al. (2021) proposed a deep reinforcement learning (DRL)-based routing protocol for mobile WSNs aimed at minimizing energy consumption and delay. The model dynamically selects optimal routing paths based on network conditions and node mobility. Experimental results showed significant improvements in network lifetime and reduced latency compared to traditional routing protocols. However, training complexity and convergence time were identified as key limitations.

Sharma and Kumar (2021) introduced a hybrid routing algorithm combining genetic algorithms (GA) and particle swarm optimization (PSO) for efficient path selection. The model optimized energy usage and routing delay simultaneously. Results demonstrated improved load balancing and reduced packet loss. However, computational overhead increased due to hybrid optimization.

Zhang et al. (2022) developed a CNN-based mobility-aware routing protocol that predicts node movement patterns and selects stable communication paths. The model improved packet delivery ratio and reduced routing overhead. However, the model required significant training data for accurate prediction.

Kumar et al. (2022) proposed a fuzzy logic-based intelligent routing mechanism integrated with machine learning for delay-sensitive applications. The model evaluated multiple parameters such as node energy, distance, and congestion to select optimal routes. Results showed reduced end-to-end delay, but scalability issues were observed in large networks.

Ahmed et al. (2023) introduced a convolutional neural network-based routing protocol focused on energy efficiency in mobile WSNs. The model learned optimal routing patterns from historical data and reduced energy consumption significantly. However, deployment challenges existed due to model complexity.

Singh et al. (2020) proposed a cluster-based routing protocol designed to improve energy efficiency in mobile WSNs. The model dynamically selects cluster heads based on residual energy and mobility patterns. Results showed increased network lifetime and reduced energy consumption. However, frequent cluster reformation due to mobility introduced additional overhead.

Alvi et al. (2021) introduced a Markov-based mobility prediction model for routing optimization in MWSNs. The model predicted node movement probabilities and selected stable routes accordingly. The results demonstrated improved routing reliability and reduced packet loss. However, prediction accuracy decreased in highly random mobility scenarios.

Raza et al. (2021) proposed a swarm intelligence-based routing protocol using ant colony optimization (ACO) to improve energy efficiency. The approach dynamically adjusted routing paths based on pheromone values and node energy levels. Results indicated improved energy efficiency and reduced delay. However, convergence time remained a limitation.

Li et al. (2022) developed an attention-based deep learning model for routing optimization in mobile WSNs. The model focused on important features such as node energy, distance, and mobility patterns to improve routing decisions. Experimental results showed enhanced routing efficiency and reduced delay. However, the model required high computational resources.

Verma et al. (2023) proposed a hybrid CNN-LSTM architecture for accurate mobility prediction in mobile WSNs. The CNN component extracted spatial features, while the LSTM captured temporal dependencies. The model significantly improved prediction accuracy and routing stability. However, increased training time was observed.

Kumar and Singh (2021) proposed an energy-aware clustering algorithm integrated with optimization techniques such as genetic algorithms to enhance routing efficiency in mobile WSNs. The model selected optimal cluster heads and minimized communication distance. Results showed improved network lifetime and reduced energy consumption. However, clustering overhead increased with node mobility.

Hassan et al. (2022) introduced a deep learning-based routing protocol designed to handle node failures and link disruptions in mobile WSNs. The model predicted potential failures and rerouted data dynamically. Experimental results demonstrated improved reliability and reduced packet loss. However, computational complexity remained a concern.

Zhang et al. (2022) proposed a reinforcement learning-based adaptive routing mechanism that learns optimal routing policies through continuous interaction with the network. The approach improved adaptability and reduced delay in dynamic environments. However, the training process required extensive iterations.

Patel et al. (2023) developed a hybrid particle swarm optimization (PSO)-based routing protocol for energy-efficient communication in MWSNs. The model optimized routing paths based on energy consumption and distance metrics. Results showed improved efficiency and reduced energy usage. However, parameter tuning affected performance.

Chen et al. (2023) proposed a causal dilated convolutional neural network model for time-series prediction of routing paths. The model effectively captured long-range dependencies in node mobility data, improving routing stability and delay performance. However, implementation complexity limited real-time deployment.

Gupta et al. (2020) proposed a QoS-aware routing protocol that considers delay, energy, and packet delivery ratio for route selection in mobile WSNs. The model dynamically adjusts routing decisions based on network conditions. Results showed improved QoS performance and reduced delay. However, increased computational overhead was observed.

Alshahrani et al. (2021) introduced a lightweight encryption-based secure routing protocol for mobile WSNs. The model ensured data confidentiality while maintaining energy efficiency. Experimental results demonstrated enhanced security with minimal overhead. However, key management complexity remained a challenge.

Meena et al. (2022) proposed a mobility-aware clustering algorithm that selects cluster heads based on node movement patterns and residual energy. The model improved stability and reduced communication overhead. Results indicated extended network lifetime, but frequent mobility changes impacted clustering efficiency.

Torres et al. (2023) developed an edge-assisted routing framework where edge nodes support routing decisions using AI-based prediction models. The system reduced latency and improved real-time decision-making. However, dependency on edge infrastructure increased system complexity.

Nair et al. (2023) proposed an attention-based deep learning model for routing optimization in MWSNs. The model prioritized critical nodes and paths based on learned importance weights. Results showed improved energy efficiency and reduced delay. However, training complexity was high.

Das et al. (2021) proposed a swarm intelligence-based routing protocol using ant colony optimization (ACO) to identify optimal paths in mobile WSNs. The model dynamically adapted to network changes and improved energy efficiency. Results showed reduced delay and enhanced packet delivery ratio. However, convergence speed remained a limitation in large-scale networks.

Ibrahim et al. (2022) introduced a hybrid framework combining machine learning and encryption techniques for secure routing in MWSNs. The model ensured data confidentiality while optimizing routing performance. Experimental results demonstrated improved security and reliability. However, encryption overhead increased computational cost.

Zhao et al. (2023) proposed a predictive routing model using deep neural networks to forecast node mobility and traffic patterns. The system proactively selected stable routes, reducing packet loss and delay. Results indicated improved routing efficiency, but the model required large datasets for training.

Fernandez et al. (2022) developed a multi-objective optimization framework using evolutionary algorithms to balance energy consumption, delay, and throughput. The model achieved improved overall performance compared to single-objective approaches. However, optimization complexity affected execution time.

Chatterjee et al. (2023) proposed a hybrid causal dilated convolutional neural network integrated with attention mechanisms for routing optimization in mobile WSNs. The model effectively captured long-range temporal dependencies and improved routing stability. Experimental results demonstrated reduced latency, enhanced energy efficiency, and improved scalability. However, model complexity and training requirements posed challenges for real-time deployment.

**Comparative Table**

| Study | Year | Technique Used | Focus Area | Advantages | Limitations |
|---|---|---|---|---|---|
| Ye et al. | 2020 | Mobility Prediction | Routing Stability | Reduced link failure | Prediction accuracy issues |
| Chen et al. | 2020 | Dilated CNN | Spatio-temporal modeling | Captures long dependencies | Complex |
| Yang et al. | 2021 | LSTM + Attention | Delay optimization | Reduced latency | Training overhead |
| Wang et al. | 2023 | CNN-RNN | Traffic prediction | High accuracy | Resource heavy |
| Ouyang et al. | 2023 | TCN | Sequence modeling | Robust prediction | Complex |

| | | | | | |
|---|---|---|---|---|---|
| Liu et al. | 2021 | DRL | Routing | Adaptive | Slow convergence |
| Sharma & Kumar | 2021 | GA + PSO | Optimization | Balanced metrics | High computation |
| Zhang et al. | 2022 | CNN | Mobility-aware routing | High PDR | Data dependency |
| Kumar et al. | 2022 | Fuzzy + ML | Delay-sensitive | Reduced delay | Scalability |
| Ahmed et al. | 2023 | CNN | Energy efficiency | Reduced energy | Complex |
| Singh et al. | 2020 | Clustering | Energy | Increased lifetime | Overhead |
| Alvi et al. | 2021 | Markov Model | Mobility prediction | Reliable | Low accuracy in randomness |
| Raza et al. | 2021 | ACO | Routing | Efficient | Slow convergence |
| Li et al. | 2022 | Attention DL | Optimization | Better decision | Complex |
| Verma et al. | 2023 | CNN-LSTM | Mobility prediction | High accuracy | Training cost |
| Kumar & Singh | 2021 | GA Clustering | Energy | Efficient | Mobility overhead |
| Hassan et al. | 2022 | DL Fault-tolerant | Reliability | Reduced loss | Complex |
| Zhang et al. | 2022 | RL | Adaptive routing | Flexible | Training cost |
| Patel et al. | 2023 | PSO | Energy routing | Efficient | Parameter tuning |
| Chen et al. | 2023 | Dilated CNN | Time-series routing | Accurate | Complex |
| Gupta et al. | 2020 | QoS routing | QoS | Improved performance | Overhead |
| Alshahrani et al. | 2021 | Encryption | Security | Secure | Key mgmt |
| Meena et al. | 2022 | Clustering | Energy | Stable | Mobility impact |
| Torres et al. | 2023 | Edge-AI | Routing | Low latency | Dependency |
| Nair et al. | 2023 | Attention DL | Energy routing | Efficient | Heavy |
| Das et al. | 2021 | ACO | Routing | Efficient | Scalability |
| Ibrahim et al. | 2022 | AI + Encryption | Security | Reliable | Latency |
| Zhao et al. | 2023 | DL | Prediction | Accurate | Data intensive |
| Fernandez et al. | 2022 | Evolutionary | Optimization | Balanced | Slow |
| Chatterjee et al. | 2023 | CD-CNN + Attention | Joint optimization | High performance | Complex |

**Conclusion**

Mobile Wireless Sensor Networks (MWSNs) represent a significant advancement in wireless communication systems, enabling flexible and dynamic data collection for applications such as environmental monitoring, smart cities, healthcare systems, and industrial automation. However, the presence of node mobility, limited battery resources, and strict delay requirements introduces major challenges in designing efficient routing protocols. This systematic review analyzed recent developments from 2020 to 2023, focusing on AI-driven routing approaches, particularly causal dilated convolutional neural networks (CD-CNNs), mobility prediction techniques, and energy-efficient routing strategies aimed at improving network performance under dynamic conditions. The review of 30 research studies highlights the increasing role of artificial intelligence in overcoming the limitations of traditional routing protocols, which are often based on static assumptions and fail in rapidly changing network environments. In contrast, AI-based models such as deep learning and reinforcement learning offer adaptive and predictive capabilities that significantly improve routing efficiency. Convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and temporal convolutional models are widely used to extract spatial–temporal features from network data. Among these, causal dilated CNNs are particularly effective due to their ability to capture long-range temporal dependencies without increasing computational complexity, making them suitable for mobility prediction and routing optimization.

Mobility prediction is a key factor in enhancing routing stability and efficiency in MWSNs. By forecasting future node positions, routing protocols can proactively select stable communication paths, thereby reducing packet loss, link failures, and network delay. Hybrid models that combine deep learning with optimization algorithms such as genetic algorithms, particle swarm optimization, and ant colony optimization further enhance energy efficiency and overall network performance. Additionally, recent studies incorporate lightweight security mechanisms and AI-based anomaly detection to ensure secure data transmission. Despite these advancements, challenges such as high computational complexity, scalability issues, real-time deployment constraints, and the need for large training datasets remain significant. Future research should focus on lightweight AI models, edge computing integration, and explainable AI techniques. Overall, AI-driven routing frameworks, especially those based on CD-CNN and mobility prediction, provide a promising direction for developing energy-efficient, delay-sensitive, and intelligent MWSNs.

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