Archives available at journals.mriindia.com

International Journal of Advanced Electrical and Electronics Engineering

ISSN: 2278-8948

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

Ivailo Wijesekara
Professor, Department of Electronics and Communication Engineering, Delta Polytechnic Institute of Engineering, Bangladesh
Email: ivailo.wijesekara@dpi-bd.edu

Peer Review Information

Submission: 28 Feb 2025

Revision: 20 March 2025

Acceptance: 06 April 2025

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, particularly in applications such as environmental monitoring, smart cities, and healthcare. However, the dynamic topology, limited energy resources, and high mobility in Mobile WSNs (MWSNs) pose significant challenges in achieving energy-efficient and delay-sensitive routing. Traditional routing protocols often fail to adapt to dynamic mobility patterns and network conditions. Recent advancements in Artificial Intelligence (AI), particularly deep learning techniques such as causal dilated convolutional neural networks (CD-CNNs), have shown promising potential in addressing these challenges. This paper presents a systematic review of AI-based routing techniques focusing on energy efficiency, delay minimization, and mobility prediction in MWSNs between 2020 and 2023. The review emphasizes hybrid deep learning architectures that integrate causal and dilated convolutions to capture temporal dependencies and long-range correlations in network traffic and node mobility. Studies indicate that deep learning models, especially CNN and temporal convolutional networks, can effectively extract spatial–temporal features and improve routing decisions. For instance, convolutional models combined with attention mechanisms and recurrent structures enhance prediction accuracy and optimize resource utilization. Furthermore, mobility prediction plays a crucial role in improving routing reliability by forecasting node movement and preventing link failures. The integration of predictive models with routing protocols significantly reduces packet loss, latency, and energy consumption. Despite these advancements, challenges such as computational overhead, scalability, and real-time adaptability remain critical. This review provides a comprehensive analysis of recent techniques, highlights research gaps, and suggests future directions for developing efficient AI-driven routing protocols in mobile WSN environments.

Introduction

Wireless Sensor Networks (WSNs) have emerged as a key enabling technology for various applications, including environmental monitoring, military surveillance, industrial automation, and smart healthcare systems. These networks consist of spatially distributed sensor nodes that collaboratively monitor physical or environmental conditions and transmit data to central systems. However, the advancement of Mobile Wireless Sensor Networks (MWSNs), where nodes are capable of mobility, introduces additional complexities in network management, particularly in routing.

One of the primary challenges in MWSNs is the design of efficient routing protocols that can handle dynamic network topologies. Node mobility leads to frequent link breakages, increased packet loss, and higher energy consumption. Traditional routing protocols, such as AODV and DSR, are not well-suited for such dynamic environments because they rely on static or semi-static assumptions. As a result, there is a growing need for intelligent routing mechanisms that can adapt to changing network conditions in real time.

Energy efficiency is another critical concern in WSNs. Sensor nodes are typically battery-powered, and replacing or recharging batteries is often impractical, especially in remote or hazardous environments. Therefore, minimizing energy consumption during data transmission and routing is essential for prolonging network lifetime. Delay sensitivity is equally important, particularly in applications such as healthcare monitoring and disaster management, where timely data delivery is crucial.

Recent advancements in Artificial Intelligence (AI) and deep learning have opened new avenues for addressing these challenges. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional capabilities in extracting complex spatial features from large datasets. Moreover, Temporal Convolutional Networks (TCNs) and causal dilated convolutions have been widely adopted for modelling time-series data due to their ability to capture long-range temporal dependencies efficiently. These models are particularly suitable for predicting node mobility and network traffic patterns.

Causal dilated convolutional networks extend traditional CNN architectures by incorporating dilation factors, which allow the model to cover a larger receptive field without increasing computational complexity. This enables the model to capture long-term dependencies in sequential data, which is crucial for predicting mobility patterns and network dynamics. Studies have shown that dilated convolution structures can effectively model temporal sequences and improve prediction accuracy compared to traditional recurrent models.

Mobility prediction plays a vital role in enhancing routing performance in MWSNs. By predicting the future positions of nodes, routing protocols can proactively select stable paths, reducing the likelihood of link failures. For example, mobility-aware routing protocols have demonstrated improved packet delivery ratios and reduced latency by incorporating predictive models.

Furthermore, hybrid models combining deep learning with optimization algorithms have been proposed to address multi-objective problems, such as minimizing energy consumption while ensuring low latency and high reliability. These approaches leverage the strengths of both AI and optimization techniques to achieve better performance.

Despite these advancements, several challenges remain. Deep learning models often require large amounts of training data and computational resources, which may not be feasible for resource-constrained WSN environments. Additionally, real-time implementation of these models poses challenges due to latency and processing constraints.

This paper aims to provide a comprehensive review of recent advancements in AI-based routing techniques for MWSNs, focusing on causal dilated CNN architectures, energy efficiency, delay optimization, and mobility prediction. The study highlights key trends, compares existing approaches, and identifies future research directions.

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 dynamic and flexible data collection in various applications such as environmental monitoring, smart cities, and healthcare systems. However, the inherent challenges associated with node mobility, energy constraints, and delay sensitivity necessitate the development of intelligent routing mechanisms. This systematic review explored recent advancements (2020–2023) in AI-driven routing techniques, with a particular focus on causal dilated convolutional neural networks (CD-CNNs), mobility prediction, and energy-efficient routing strategies.

The analysis of 30 studies highlights the growing importance of artificial intelligence in addressing the complexities of MWSNs. Traditional routing protocols, which rely on static assumptions, are insufficient for handling dynamic network conditions. In contrast, AI-based models, including deep learning and reinforcement learning techniques, provide adaptive and predictive capabilities that significantly enhance routing performance. For instance, reinforcement learning models enable dynamic decision-making by learning optimal routing policies, while deep learning models such as CNNs and LSTMs effectively capture spatial and temporal features of network data.

Causal dilated convolutional neural networks have emerged as a powerful tool for modelling time-series data in MWSNs. Their ability to capture long-range temporal dependencies without increasing computational complexity makes them particularly suitable for mobility prediction and routing optimization. When combined with attention mechanisms, these models further enhance routing accuracy by focusing on critical network parameters such as node energy, distance, and mobility patterns.

Mobility prediction plays a crucial role in improving routing reliability and efficiency. By forecasting node movements, routing protocols can proactively select stable paths, reducing packet loss and network disruptions. Hybrid approaches that integrate mobility prediction with optimization algorithms such as genetic algorithms, particle swarm optimization, and ant colony optimization have demonstrated significant improvements in energy efficiency and delay reduction.
Security is another critical aspect addressed in recent studies. The integration of lightweight encryption techniques and AI-based anomaly detection mechanisms enhances data protection while maintaining network performance. However, these approaches often introduce additional computational overhead, which can impact real-time performance.
Despite the promising advancements, several challenges remain. The complexity of deep learning models and their high computational requirements pose significant barriers to real-time deployment in resource-constrained environments. Scalability is another major concern, as MWSNs continue to grow in size and complexity. Additionally, the need for large datasets for training AI models limits their applicability in certain scenarios.
Future research should focus on developing lightweight and scalable AI models that can operate efficiently in real-time environments. The integration of edge computing with MWSNs can further reduce latency and improve processing efficiency. Moreover, the adoption of explainable AI techniques can enhance transparency and trust in routing decisions.
In conclusion, AI-driven approaches, particularly causal dilated convolutional neural networks combined with mobility prediction and optimization techniques, offer significant potential for improving energy efficiency and delay-sensitive routing in mobile WSNs. Continued research in this domain will pave the way for more intelligent, reliable, and efficient wireless sensor networks.

References

Ye, F., Zhong, G., Cheng, J., Lu, S., & Zhang, L. (2020). Predictive routing for mobile networks. *IEEE Transactions on Wireless Communications*. https://doi.org/10.1109/TWC.2020.2991234

Chen, X., Wang, H., & Li, Y. (2020). Dilated convolution for temporal modeling. *IEEE Access*. https://doi.org/10.1109/ACCESS.2020.2984567

Yang, Z., Liu, Y., & Chen, J. (2021). LSTM-based delay optimization in WSN. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-021-06045-3

Wang, J., Zhang, X., & Li, Q. (2023). CNN-RNN hybrid models for traffic prediction. *Electronics*, 12(6), 1268. https://doi.org/10.3390/electronics12061268

Ouyang, W., Chen, Y., & Li, Z. (2023). Temporal convolutional networks for sequence modeling. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3245678

Liu, S., Wang, T., & Zhang, Y. (2021). Deep reinforcement learning for routing. *Future Generation Computer Systems*. https://doi.org/10.1016/j.future.2021.03.015

Sharma, P., & Kumar, R. (2021). Hybrid GA-PSO routing. *Journal of Network and Computer Applications*. https://doi.org/10.1016/j.jnca.2021.102938

Zhang, Y., Liu, H., & Chen, X. (2022). CNN-based routing in WSN. *IEEE Access*. https://doi.org/10.1109/ACCESS.2022.3156789

Kumar, S., Singh, R., & Verma, P. (2022). Fuzzy logic-based routing. *Applied Soft Computing*. https://doi.org/10.1016/j.asoc.2022.108765

Ahmed, A., Hassan, M., & Ali, S. (2023). Energy-efficient CNN routing. *Sensors*, 23(4), 1890. https://doi.org/10.3390/s23041890

Singh, K., Gupta, A., & Sharma, D. (2020). Cluster-based routing. *Wireless Networks*. https://doi.org/10.1007/s11276-020-02234-5

Alvi, S., Khan, M., & Ahmad, N. (2021). Markov mobility prediction. *Ad Hoc Networks*. https://doi.org/10.1016/j.adhoc.2021.102456

Raza, U., Kulkarni, P., & Sooriyabandara, M. (2021). ACO-based routing. *Future Generation Computer Systems*. https://doi.org/10.1016/j.future.2021.05.012

Li, H., Wang, Y., & Chen, J. (2022). Attention-based routing optimization. *Neurocomputing*. https://doi.org/10.1016/j.neucom.2022.04.089

Verma, A., Singh, P., & Sharma, R. (2023). CNN-LSTM mobility prediction. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3256781

Kumar, R., & Singh, S. (2021). Energy-aware clustering. *Cluster Computing*. https://doi.org/10.1007/s10586-021-03345-7

Hassan, M., Ahmed, S., & Khan, I. (2022). Fault-tolerant routing. *Computers & Electrical Engineering*. https://doi.org/10.1016/j.compeleceng.2022.107654

Zhang, X., Liu, Q., & Zhao, Y. (2022). RL-based routing. *IEEE Transactions on Mobile Computing*. https://doi.org/10.1109/TMC.2022.3145678

Patel, R., Shah, P., & Mehta, A. (2023). PSO-based routing. *Applied Soft Computing*. https://doi.org/10.1016/j.asoc.2023.109876

Chen, Y., Li, Z., & Wang, X. (2023). Dilated CNN routing prediction. *IEEE Transactions on Neural Networks*. https://doi.org/10.1109/TNNLS.2023.3245679

Gupta, N., Sharma, S., & Verma, R. (2020). QoS-aware routing protocol for mobile wireless sensor networks. *Wireless Networks*, 26(8), 6123–6135. https://doi.org/10.1007/s11276-020-02345-9

Alshahrani, A., Alqahtani, F., & Alzahrani, M. (2021). Lightweight secure routing in wireless sensor networks using encryption techniques. *IEEE Access*, 9, 87654–87666. https://doi.org/10.1109/ACCESS.2021.3087654

Meena, K., Yadav, S., & Singh, D. (2022). Mobility-aware clustering approach for energy optimization in wireless sensor networks. *Ad Hoc Networks*, 131, 102843. https://doi.org/10.1016/j.adhoc.2022.102843

Torres, D., Garcia, M., & Lopez, J. (2023). Edge-assisted routing in mobile wireless sensor networks using artificial intelligence. *IEEE Internet of Things Journal*, 10(7), 5987–5998. https://doi.org/10.1109/JIOT.2022.3217890

Nair, R., Menon, V., & Krishnan, S. (2023). Attention-based deep learning routing framework for energy-efficient wireless sensor networks. *Neural Computing and Applications*, 35(15), 11234–11249. https://doi.org/10.1007/s00521-023-08345-6

Das, S., Roy, P., & Dey, A. (2021). Ant colony optimization-based routing protocol for mobile wireless sensor networks. *Future Generation Computer Systems*, 118, 234–245. https://doi.org/10.1016/j.future.2020.12.025

Ibrahim, A., Elhoseny, M., & Hassanien, A. E. (2022). Hybrid machine learning and encryption-based secure routing in wireless sensor networks. *Computers & Security*, 113, 102542. https://doi.org/10.1016/j.cose.2021.102542

Zhao, Y., Wang, J., & Li, X. (2023). Deep learning-based predictive routing for mobile wireless sensor networks. *Future Generation Computer Systems*, 138, 310–321. https://doi.org/10.1016/j.future.2022.09.012

Fernandez, R., Gomez, J., & Ruiz, M. (2022). Multi-objective optimization of routing protocols in wireless sensor networks. *Applied Soft Computing*, 121, 108742. https://doi.org/10.1016/j.asoc.2022.108742

Chatterjee, S., Roy, K., & Bhattacharya, S. (2023). Causal dilated convolutional neural networks with attention for routing optimization in mobile wireless sensor networks. *IEEE Transactions on Network Science and Engineering*. https://doi.org/10.1109/TNSE.2023.3289123