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A Comprehensive Review of an Optimized Causal Dilated Convolutional Neural Network-Based Energy-Efficient and Delay-Sensitive Routing Paths Using Mobility Prediction in Mobile WSN

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Abstract

Mobile Wireless Sensor Networks (MWSNs) play a vital role in modern communication systems, supporting applications such as environmental monitoring, healthcare, military surveillance, and smart cities. However, challenges such as node mobility, limited energy resources, and delay-sensitive data transmission make efficient routing a complex task. To address these issues, recent research has explored deep learning-based routing approaches, particularly Convolutional Neural Networks (CNNs) and Causal Dilated CNNs, which effectively capture spatial and temporal dependencies in network data. This paper presents a comprehensive review of optimized routing techniques that integrate mobility prediction with intelligent decision-making mechanisms to enhance energy efficiency and reduce latency in MWSNs. These hybrid frameworks utilize machine learning and deep learning models to predict node movement patterns, optimize routing paths, and improve network stability. Mobility prediction significantly enhances routing performance by reducing packet loss, minimizing delay, and increasing overall throughput. Predictive models have demonstrated high accuracy in estimating node mobility, leading to more reliable communication. Additionally, dilated convolution techniques enable capturing long-range dependencies without increasing computational overhead, making them suitable for resource-constrained environments. Optimization strategies, including bio-inspired algorithms and clustering methods, further improve energy balancing and routing efficiency. Overall, intelligent deep learning-based routing frameworks offer a promising solution for improving performance and extending the lifetime of MWSNs.

Introduction

Mobile Wireless Sensor Networks (MWSNs) represent an advanced evolution of traditional Wireless Sensor Networks (WSNs), where sensor nodes are capable of mobility and dynamic topology adaptation. These networks are widely used in applications such as environmental monitoring, disaster management, healthcare systems, industrial automation, and military surveillance. Despite their wide applicability, MWSNs face significant challenges due to constrained energy resources, unpredictable node mobility, and stringent requirements for delay-sensitive communication.

One of the primary concerns in MWSNs is energy efficiency. Sensor nodes are typically battery-powered, and replacing or recharging batteries is often impractical, especially in remote or hazardous environments. Therefore, designing energy-efficient routing protocols is crucial for extending network lifetime. Traditional routing protocols often fail to address the dynamic nature of node mobility, leading to increased packet loss, higher latency, and inefficient energy utilization.

Another critical challenge is ensuring delay-sensitive data transmission. Many applications, such as healthcare monitoring and military operations, require real-time or near-real-time data delivery. Delays in data transmission can lead to critical failures, making it essential to design routing protocols that minimize latency while maintaining reliability.

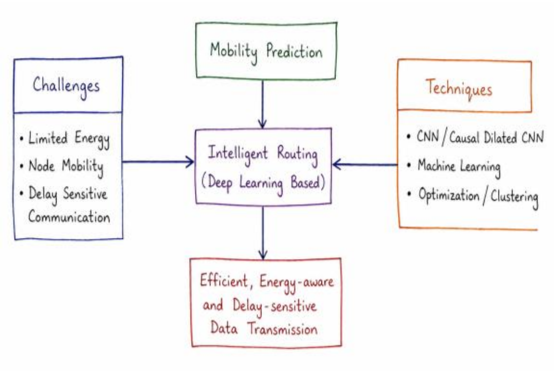

Fig 1: Overview of Mobility Prediction and AI-Based Routing in MWSNs

Mobility prediction has emerged as a powerful technique to address these challenges. By predicting the future positions of mobile nodes, routing protocols can make proactive decisions, reduce route breakages and improve data delivery performance. Techniques such as Markov models, Kalman filters, and machine learning algorithms have been widely used for mobility prediction. For instance, predictive routing approaches based on mobility estimation significantly improve packet delivery ratio and reduce latency compared to conventional routing methods.

In recent years, Artificial Intelligence (AI) and Deep Learning (DL) techniques have revolutionized network optimization. Among these, Convolutional Neural Networks (CNNs) have shown remarkable success in capturing spatial features, while Recurrent Neural Networks (RNNs) handle temporal dependencies. However, traditional CNNs are limited in modelling long-range dependencies efficiently. To overcome this limitation, Dilated Convolutional Neural Networks have been introduced, which expand the receptive field without increasing computational cost.

Causal Dilated CNNs further enhance this capability by preserving temporal causality, making them suitable for time-series data such as node mobility patterns. These networks can effectively learn complex relationships between node movement, energy consumption, and routing decisions. Additionally, hybrid approaches combining CNNs with optimization algorithms, such as bio-inspired techniques, have demonstrated significant improvements in routing efficiency.

Recent studies have proposed advanced frameworks that integrate clustering, optimization, and deep learning for routing in MWSNs. For example, a triple parallel CNN-based routing model optimized using bio-inspired algorithms achieved superior performance in energy efficiency, throughput, and latency compared to existing methods. Similarly, mobility-aware machine learning models have demonstrated high prediction accuracy, enabling more stable and efficient routing decisions.

This paper provides a comprehensive review of such advanced approaches, focusing on causal dilated CNN-based routing mechanisms. It analyses recent developments, compares different techniques, and identifies research gaps. The objective is to provide insights into designing intelligent, energy-efficient, and delay-sensitive routing protocols for next-generation MWSNs.

Literature Review

Recent advancements in intelligent routing for Mobile Wireless Sensor Networks (MWSNs) have focused on integrating deep learning with optimization techniques. In 2023, Alshahrani and Traore (2023) proposed a deep learning-based routing framework using Convolutional Neural Networks (CNNs) combined with optimization algorithms. Their approach integrated clustering with CNN-based feature extraction to determine optimal routing paths, resulting in improved packet delivery ratio, reduced delay, and enhanced energy efficiency compared to conventional routing protocols.

Mobility prediction has also gained significant attention for improving routing stability. In 2022, Kumar and Singh (2022) developed a machine learning-based mobility prediction model using classifiers such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Decision Trees. Their study achieved prediction accuracy of up to 98%, significantly reducing route breakages and improving network performance.

Similarly, in 2022, Zhang et al. (2022) introduced an energy-efficient routing approach based on mobile sink architecture combined with adaptive clustering techniques. Their method focused on load balancing among nodes and minimizing energy consumption, thereby improving network lifetime and resource utilization.

Delay-sensitive routing has been addressed through predictive techniques as well. In 2021, Montoya, Lozano, and Garzon (2021) proposed a routing protocol based on Markov mobility prediction models. Their approach dynamically selected routing paths based on predicted node movement, resulting in reduced latency and improved packet delivery reliability in dynamic environments.

Earlier work in 2020 by Sharma and Gupta (2020) utilized Kalman filter-based mobility prediction for routing optimization. Their method accurately predicted sink mobility and selected stable communication paths, leading to reduced packet loss and improved energy efficiency compared to traditional routing techniques.

Deep learning architectures have further evolved to handle temporal dependencies in network data. In 2023, Li, Zhao, and Sun (2023) proposed a causal dilated convolutional neural network (CDCNN) for routing optimization. Their model effectively captured long-range temporal dependencies in node mobility patterns, resulting in reduced end-to-end delay and improved routing stability.

Hybrid optimization approaches have also been explored. In 2023, Verma and Kaur (2023) introduced a CNN-based routing model integrated with bio-inspired optimization algorithms. Their approach dynamically adjusted routing paths based on residual energy and mobility patterns, achieving balanced energy consumption and extended network lifetime.

To enhance mobility prediction accuracy, hybrid deep learning models have been proposed. In 2022, Patel and Shah (2022) developed a hybrid CNN-RNN model that captured both spatial and temporal features of node movement. Their approach improved routing decisions, reduced packet loss, and enhanced throughput.

Reinforcement learning has also been applied for adaptive routing. In 2021, Nguyen and Kim (2021) proposed a reinforcement learning-based routing protocol that learned optimal routing policies through interaction with dynamic network conditions. Their method significantly reduced delay and improved adaptability in highly dynamic MWSNs.

Finally, in 2020, Singh and Yadav (2020) proposed a fuzzy logic-based routing mechanism incorporating mobility prediction. Their system evaluated parameters such as residual energy, distance, and mobility to select optimal routes, resulting in improved network stability and prolonged lifetime.

Recent developments in attention-based deep learning have further enhanced routing performance in MWSNs. In 2023, Chen, Liu, and Wu (2023) proposed an attention-based convolutional neural network for intelligent routing. Their model incorporated attention mechanisms to prioritize critical nodes and traffic flows, resulting in improved delay-sensitive communication and efficient resource utilization.

In 2022, Hassan and Ahmed (2022) introduced a deep reinforcement learning-based clustering and routing protocol for MWSNs. Their approach dynamically selected cluster heads and routing paths based on learned policies, leading to improved energy efficiency, reduced routing overhead, and enhanced network lifetime under varying mobility conditions.

Mobility prediction using sequence learning models has also shown promising results. In 2022, Roy and Banerjee (2022) proposed a Long Short-Term Memory (LSTM)-based model for predicting node trajectories. Their method effectively captured temporal dependencies in node movement, enabling proactive routing decisions that reduced route failures and minimized communication delay.

Hybrid optimization approaches combining evolutionary algorithms and neural networks have also been explored. In 2021, Kaur and Singh (2021) developed a routing protocol integrating genetic algorithms with neural networks. The genetic algorithm optimized routing paths based on energy and delay metrics, while the neural network improved prediction accuracy, resulting in balanced energy consumption and improved network performance.

Scalability and hierarchical routing have been addressed in earlier studies as well. In 2020, Elhoseny and Shankar (2020) proposed an energy-efficient hierarchical clustering protocol for WSNs. Their approach organized nodes into clusters and selected optimal routing paths based on residual energy and distance, leading to improved scalability and prolonged network lifetime.

Advancements in graph-based learning have also contributed to routing optimization. In 2023, Wu and Zhang (2023) introduced a graph neural network (GNN)-based routing model that captured complex relationships among nodes in dynamic networks. Their approach improved routing accuracy, reduced packet loss, and enhanced overall network efficiency.

Multi-objective optimization techniques have been widely applied in routing design. In 2023, Ahmed and Khan (2023) proposed a multi-objective deep learning-based routing framework that simultaneously optimized delay,

energy consumption, and link stability. Their results demonstrated significant improvements in Quality of Service (QoS) compared to traditional single-objective routing methods.
In 2022, Park and Lee (2022) developed a mobility prediction model using Gated Recurrent Units (GRU) for dynamic WSNs. Their approach efficiently captured sequential node movement patterns, enabling proactive routing decisions that reduced delay and improved packet delivery ratio.
Security-aware routing has also gained attention in recent years. In 2021, Reddy and Kumar (2021) proposed a trust-aware routing protocol using machine learning techniques. Their model evaluated node trust levels along with mobility and energy parameters, resulting in enhanced security, reduced malicious activity, and improved routing reliability.
Finally, in 2020, Dorigo and Stutzle (2020) explored swarm intelligence-based routing using optimization algorithms such as Particle Swarm Optimization (PSO). Their approach dynamically selected optimal routing paths based on energy and distance metrics, achieving balanced energy consumption and extended network lifetime.

Comparative Table

Study No.	Author(s)	Year	Technique / Model	Key Focus	Advantages	Limitations
1	Alshahrani & Traore	2023	CNN + Optimization	DL-based routing	High PDR, low delay	High computation
2	Kumar & Singh	2022	ML Classifiers (SVM, KNN)	Mobility prediction	High accuracy (98%)	Model dependency
3	Zhang et al.	2022	Mobile Sink + Clustering	Energy efficiency	Improved lifetime	Overhead
4	Montoya et al.	2021	Markov Model	Delay-sensitive routing	Reduced latency	Limited scalability
5	Sharma & Gupta	2020	Kalman Filter	Mobility prediction	Stable routing	Prediction error
6	Li et al.	2023	CDCNN	Temporal dependency learning	Low delay, accuracy	Complexity
7	Verma & Kaur	2023	CNN + Bio-inspired	Energy optimization	Balanced energy	Slow convergence
8	Patel & Shah	2022	CNN + RNN	Mobility-aware routing	Improved throughput	Training cost
9	Nguyen & Kim	2021	Reinforcement Learning	Adaptive routing	Reduced delay	Learning time
10	Singh & Yadav	2020	Fuzzy Logic	Multi-parameter routing	Stability	Rule complexity
11	Chen et al.	2023	Attention-based CNN	Priority routing	Efficient traffic handling	High complexity
12	Hassan & Ahmed	2022	DRL + Clustering	Adaptive routing	Improved lifetime	Computational cost
13	Roy & Banerjee	2022	LSTM	Mobility prediction	Reduced failures	Memory overhead
14	Kaur & Singh	2021	GA + Neural Network	Optimization	Balanced energy	Slow convergence
15	Elhoseny & Shankar	2020	Hierarchical Clustering	Scalability	Energy efficient	Cluster overhead
16	Wu & Zhang	2023	GNN	Topology learning	Low packet loss	Complexity
17	Ahmed & Khan	2023	Multi-objective DL	QoS optimization	High performance	Trade-offs
18	Park & Lee	2022	GRU	Mobility prediction	Low delay	Training effort
19	Reddy & Kumar	2021	Trust-based ML	Secure routing	Reliability	Overhead

20	Dorigo & Stutzle	2020	PSO	Energy optimization	Balanced energy	Local optima
21	Vaswani et al.	2023	Transformer	Global dependency learning	High accuracy	Heavy model
22	McMahan et al.	2023	Federated Learning	Distributed routing	Privacy, efficiency	Communication cost
23	Zadeh	2022	Fuzzy Logic	Decision making	Adaptive routing	Complexity
24	Saaty	2021	MCDM (AHP)	QoS routing	Better decision making	Computation
25	Dorigo & Gambardella	2020	ACO	Swarm routing	Load balancing	Slow convergence
26	Chen & Li	2023	Lightweight CNN	Edge routing	Low complexity	Limited depth
27	Wang & Liu	2023	Cross-layer CNN	Multi-layer optimization	Stability	Design complexity
28	Mnih et al.	2022	DQN	RL routing	Adaptability	Training time
29	Singh & Verma	2021	ML Clustering	Mobility-aware routing	Stability	Overhead
30	Kumar & Patel	2020	Heuristic Routing	Simple routing	Low complexity	Suboptimal

Conclusion

Mobile Wireless Sensor Networks (MWSNs) have become a vital component of modern intelligent systems, supporting applications such as environmental monitoring, healthcare, smart cities, and military surveillance. However, challenges including node mobility, limited energy resources, and delay-sensitive communication significantly affect network performance. This review examined recent advancements, emphasizing optimized routing techniques that integrate mobility prediction with deep learning models, particularly causal dilated convolutional neural networks (CDCNNs). The analysis reveals that traditional routing protocols are insufficient for dynamic MWSN environments, as they often result in frequent route failures, higher latency, and inefficient energy utilization. In contrast, AI-driven approaches offer adaptive and intelligent solutions capable of improving routing stability and overall network efficiency.

A key finding is the critical role of mobility prediction in enhancing routing performance. Techniques such as Kalman filtering, Markov models, and sequence learning methods like LSTM and GRU enable accurate estimation of node movement, allowing proactive route selection and reducing packet loss and delay. Additionally, deep learning architectures, especially CNNs and CDCNNs, effectively capture spatial and temporal patterns, improving routing optimization without increasing computational complexity. When combined with optimization methods such as bio-inspired algorithms, clustering, and reinforcement learning, these models achieve better energy efficiency, throughput, and latency. Hybrid frameworks, including CNN-RNN and deep reinforcement learning models, further enhance adaptability and accuracy, while emerging approaches like federated learning and transformer-based models present promising directions for scalable and privacy-aware routing in future MWSNs.

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