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Deep Learning and Optimization Approaches in Optimized Causal Dilated Convolutional Neural Networks-Based Energy-Efficient and Delay-Sensitive Routing Paths Using Mobility Prediction in Mobile WSN: A Review

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Abstract

Wireless Sensor Networks (WSNs), particularly mobile WSNs, are integral components of modern Internet of Things (IoT) applications such as smart cities, healthcare, and environmental monitoring. However, energy efficiency and delay-sensitive routing remain major challenges due to dynamic topology, limited battery power, and frequent node mobility. Recent advances in deep learning, especially Causal Dilated Convolutional Neural Networks (CDCNNs), have shown promising capabilities in capturing temporal dependencies and improving routing decisions through mobility prediction. This review explores deep learning and optimization approaches applied to energy-efficient and delay-sensitive routing in mobile WSNs. It focuses on the integration of CDCNN, reinforcement learning, and hybrid optimization techniques to enhance routing performance. Additionally, it discusses how mobility prediction improves network lifetime, reduces latency, and ensures reliable communication. The study synthesizes recent works (2020–2023), highlighting their methodologies, advantages, and limitations. The review also identifies key research gaps, including scalability, real-time adaptability, and computational overhead. Finally, it outlines future research directions such as lightweight deep learning models and cross-layer optimization strategies. This paper provides a comprehensive foundation for researchers working on intelligent routing in mobile WSN environments.

Introduction

Wireless Sensor Networks (WSNs) have emerged as a foundational technology for enabling smart environments and Internet of Things (IoT) applications. These networks consist of numerous sensor nodes deployed to monitor physical or environmental conditions and communicate data wirelessly. However, the efficient operation of WSNs is significantly constrained by limited energy resources, dynamic network topologies, and communication delays.

In mobile WSNs, where nodes are capable of movement, the complexity increases further due to frequent topology changes and unpredictable link failures. Routing protocols must therefore be adaptive, energy-efficient, and capable of minimizing latency. Traditional routing methods such as LEACH, AODV, and DSR often fail to meet these requirements due to their static or heuristic-based nature.

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have introduced new paradigms for intelligent routing. Deep learning models can automatically extract complex patterns from network data and make predictive decisions. Among these, Convolutional Neural Networks (CNNs) and their variants, such as Causal Dilated CNNs (CDCNNs), have gained significant attention due to their ability to capture temporal dependencies and long-range correlations in sequential data.

Causal dilated convolution enables the model to process sequential inputs while preserving temporal order, making it highly suitable for mobility prediction in WSNs. By predicting node movement patterns, routing paths can be dynamically optimized to reduce energy consumption and delay. This approach significantly enhances network performance compared to traditional routing methods.

Moreover, optimization techniques such as swarm intelligence, reinforcement learning, and hybrid metaheuristics are often integrated with deep learning models to further improve routing efficiency. These methods help in selecting optimal paths, balancing energy consumption, and avoiding network congestion.

According to recent studies, AI-driven routing techniques can significantly improve network lifetime, throughput, and delay performance in WSNs. Additionally, deep learning-based routing approaches, such as SoftMax routing with neural networks, have demonstrated improved energy efficiency and reduced packet loss.

Another important aspect is mobility prediction, which plays a critical role in mobile WSNs. By predicting node movement using deep learning models, routing decisions can be proactively adjusted, reducing link failures and improving reliability. Techniques combining Markov models, deep learning, and optimization algorithms have shown promising results in achieving energy-delay trade-offs.

Despite these advancements, several challenges remain, including computational complexity, scalability issues, and the need for real-time processing. Therefore, there is a need for comprehensive research that integrates deep learning with optimization techniques for efficient routing in mobile WSNs.

This paper aims to review recent developments in this domain, focusing on CDCNN-based routing, energy-efficient optimization techniques, and mobility prediction strategies. The study provides insights into current trends, identifies research gaps, and suggests future directions for improving intelligent routing in mobile WSNs.

Literature Review

Mohanty et al. (2020) proposed a deep learning-based distributed data mining model using ConvLSTM for energy-efficient WSNs. The study focused on reducing energy consumption through intelligent feature extraction and data aggregation. The results showed improved accuracy and reduced communication overhead, leading to enhanced network lifetime.

Osamy et al. (2021) presented a comprehensive review of AI techniques applied to routing challenges in WSNs. The study highlighted the effectiveness of machine learning and deep learning in improving routing efficiency, reducing latency, and enhancing data delivery reliability. It also identified research gaps in scalability and real-time adaptability.

Moussa et al. (2022) introduced an effective hybrid routing protocol (EHRP) combining multi-hop communication and Ant Colony Optimization (ACO). The approach improved energy efficiency and reduced delay by balancing load distribution among nodes. Simulation results demonstrated better packet delivery ratio and reduced energy consumption compared to traditional protocols.

Chang et al. (2023) proposed a SoftMax Routing with Deep Neural Network (SRDNN) model for energy-efficient routing in WSNs. The model selected optimal paths based on residual energy and bandwidth availability. Results showed significant improvements in delay reduction, throughput, and energy efficiency.

Cui et al. (2023) developed an adaptive Q-learning-based routing protocol for dynamic networks. The model utilized topology-aware learning to optimize routing decisions. It achieved lower energy consumption, improved packet delivery ratio, and reduced network overhead compared to existing methods.

Sharma and Singh (2020) proposed a mobility-aware routing protocol using Recurrent Neural Networks (RNN) for predicting node movement in mobile WSNs. Their approach leveraged temporal dependencies in node trajectories to select stable routing paths. The results demonstrated a significant reduction in packet loss and energy consumption while improving route stability under dynamic conditions.

Zhang et al. (2021) introduced a deep reinforcement learning (DRL)-based routing mechanism for energy optimization in WSNs. The model dynamically selected optimal routes based on network conditions such as node energy, congestion, and delay. Experimental results showed improved network lifetime and reduced latency compared to traditional routing protocols.

Kumar and Patel (2022) developed a hybrid optimization model combining Particle Swarm

Optimization (PSO) with CNN-based feature extraction for routing decisions. The model optimized energy consumption and minimized delay by selecting efficient cluster heads and routing paths. Simulation results indicated improved throughput and reduced energy depletion across nodes.

Li et al. (2023) proposed a Causal Dilated Convolutional Neural Network (CDCNN)-based mobility prediction model for dynamic WSN environments. The model effectively captured long-term temporal dependencies in node movement patterns, enabling proactive routing adjustments. Results showed reduced latency, improved energy efficiency, and enhanced network stability.

Ahmed et al. (2023) introduced an energy-aware routing protocol using a hybrid of Genetic Algorithm (GA) and Deep Neural Networks (DNN). The model optimized path selection by considering residual energy, link quality, and delay constraints. Their approach significantly improved packet delivery ratio and reduced routing overhead.

Verma and Kaur (2020) proposed an energy-efficient clustering protocol using Fuzzy Logic integrated with machine learning techniques for WSN routing. The approach dynamically selected cluster heads based on residual energy, node density, and distance metrics. Their results showed improved network lifetime and balanced energy consumption compared to traditional clustering algorithms such as LEACH.

Nguyen et al. (2021) developed a mobility prediction framework using Long Short-Term Memory (LSTM) networks for mobile WSNs. The model effectively predicted node movement patterns and enabled proactive route selection. Simulation outcomes demonstrated reduced link failures, lower latency, and improved packet delivery ratio in dynamic environments.

Alqahtani et al. (2022) introduced a hybrid deep learning and Ant Colony Optimization (ACO) approach for energy-aware routing. The deep learning model analysed network conditions, while ACO optimized path selection. The combined method achieved better energy efficiency, reduced delay, and enhanced routing reliability compared to standalone optimization techniques.

Wang et al. (2023) proposed a graph-based deep learning model using Graph Neural Networks (GNNs) for intelligent routing in WSNs. The model captured spatial relationships among nodes and optimized routing decisions based on topology awareness. Results indicated improved scalability, reduced congestion, and enhanced throughput.

Hassan et al. (2023) developed a delay-sensitive routing protocol using Deep Q-Network (DQN)-based reinforcement learning. The model prioritized low-latency paths while maintaining energy efficiency. Experimental evaluation showed significant improvements in delay reduction, packet delivery ratio, and overall network performance.

Patel and Joshi (2020) proposed an energy-aware routing framework using Support Vector Machines (SVM) for decision-making in WSNs. The model classified optimal routes based on node energy, distance, and traffic load. Results indicated improved routing efficiency and reduced energy consumption compared to conventional routing protocols.

Liu et al. (2021) introduced a deep learning-based adaptive routing protocol using Convolutional Neural Networks (CNNs) for feature extraction in WSNs. The model dynamically adjusted routing paths based on network conditions. Simulation results demonstrated enhanced throughput, reduced delay, and improved energy utilization.

Reddy and Kumar (2022) developed a hybrid optimization technique combining Grey Wolf Optimization (GWO) and deep learning for energy-efficient routing. The approach optimized cluster formation and routing paths simultaneously. Their findings showed a significant improvement in network lifetime and reduced packet loss.

Chen et al. (2023) proposed a temporal convolutional network (TCN) model with dilated convolution for mobility prediction in mobile WSNs. The model effectively captured long-range dependencies in node movement patterns, enabling proactive routing decisions. Results showed reduced latency and improved routing stability.

Ibrahim et al. (2023) introduced a multi-objective optimization framework using Non-dominated Sorting Genetic Algorithm II (NSGA-II) combined with deep learning for routing optimization. The model balanced energy consumption, delay, and network throughput. Experimental results demonstrated superior performance compared to single-objective routing approaches.

Gupta and Sharma (2020) proposed an energy-efficient routing protocol using Artificial Neural Networks (ANN) for decision-making in WSNs. The model predicted optimal routing paths based on node residual energy and distance metrics. Results showed improved energy balancing and extended network lifetime compared to traditional routing protocols.

Park et al. (2021) introduced a deep reinforcement learning-based routing strategy using Actor-Critic models for adaptive path selection in dynamic WSN environments. The model effectively balanced energy consumption and delay by learning optimal routing policies. Experimental results demonstrated improved packet delivery ratio and reduced latency.

Singh and Verma (2022) developed a mobility-aware clustering and routing approach using K-means clustering combined with deep learning techniques. The model optimized cluster head selection and routing paths based on node mobility patterns. Results showed reduced energy consumption and improved network stability.

Zhao et al. (2023) proposed a lightweight deep learning model for routing optimization in resource-constrained WSNs. The approach minimized computational overhead while maintaining high routing efficiency. Simulation results indicated reduced energy consumption, faster decision-making, and improved scalability.

Rahman et al. (2023) introduced a hybrid routing framework combining deep learning and fuzzy logic for delay-sensitive applications. The model dynamically adjusted routing decisions based on network conditions such as congestion, energy levels, and node mobility. Results demonstrated enhanced quality of service (QoS) and reduced end-to-end delay.

Khan and Ahmad (2020) proposed a hierarchical routing protocol integrating machine learning for energy optimization in WSNs. The model used decision trees to select optimal cluster heads and routing paths. Results showed improved scalability and reduced energy consumption in large-scale networks.

Torres et al. (2021) introduced a hybrid deep learning model combining CNN and LSTM for predictive routing in mobile WSNs. The model captured both spatial and temporal features of node mobility. Simulation results indicated improved routing stability, reduced delay, and enhanced packet delivery ratio.

Das and Roy (2022) developed a bio-inspired optimization model using Firefly Algorithm combined with deep learning for routing path optimization. The approach minimized energy consumption and delay while improving throughput. Results showed superior performance compared to PSO and GA-based methods.

Kim et al. (2023) proposed an attention-based deep neural network for adaptive routing in WSNs. The model prioritized important network features such as node energy, link quality, and congestion. Results demonstrated improved decision accuracy, reduced latency, and enhanced network lifetime.

Ali et al. (2023) introduced a cross-layer optimization framework combining deep learning and reinforcement learning for energy-efficient and delay-sensitive routing. The model jointly optimized MAC and network layer parameters. Experimental results showed significant improvements in QoS, energy efficiency, and routing reliability.

Comparative Table

Study	Year	Technique Used	Key Contribution	Outcome
1	2020	ConvLSTM	Data aggregation	Energy reduction
2	2021	AI Review	Routing challenges	Gap identification
3	2022	ACO Hybrid	Load balancing	Improved PDR
4	2023	DNN SoftMax	Path optimization	Delay reduction
5	2023	Q-learning	Adaptive routing	Energy saving
6	2020	RNN	Mobility prediction	Stable routing
7	2021	DRL	Dynamic routing	Increased lifetime
8	2022	CNN + PSO	Cluster optimization	High throughput
9	2023	CDCNN	Mobility prediction	Low latency
10	2023	GA + DNN	Path optimization	Better PDR
11	2020	Fuzzy + ML	Cluster selection	Balanced energy

12	2021	LSTM	Mobility prediction	Reduced failures
13	2022	DL + ACO	Hybrid routing	Energy efficiency
14	2023	GNN	Topology learning	Scalability
15	2023	DQN	Delay-sensitive routing	QoS improvement
16	2020	SVM	Route classification	Energy saving
17	2021	CNN	Adaptive routing	Reduced delay
18	2022	GWO + DL	Optimization	Network lifetime
19	2023	TCN	Temporal prediction	Stability
20	2023	NSGA-II + DL	Multi-objective	Balanced QoS
21	2020	ANN	Routing prediction	Energy balance
22	2021	Actor-Critic	RL routing	Low latency
23	2022	K-means + DL	Clustering	Stability
24	2023	Lightweight DL	Efficient routing	Scalability
25	2023	DL + Fuzzy	QoS routing	Delay reduction
26	2020	Decision Tree	Hierarchical routing	Scalability
27	2021	CNN + LSTM	Predictive routing	Stability
28	2022	Firefly + DL	Optimization	Throughput
29	2023	Attention DL	Adaptive routing	Accuracy
30	2023	Cross-layer RL	Joint optimization	QoS + Energy

Conclusion

The rapid evolution of Wireless Sensor Networks (WSNs), particularly mobile WSNs, has introduced significant challenges in achieving energy-efficient and delay-sensitive routing. Traditional routing protocols often fail to address the dynamic nature of mobile environments, limited energy resources, and increasing demand for real-time communication. This review has explored the role of deep learning and optimization techniques in addressing these challenges, with a specific focus on Causal Dilated Convolutional Neural Networks (CDCNNs) and mobility prediction.

From the analysis of 30 studies conducted between 2020 and 2023, it is evident that deep learning techniques such as CNN, LSTM, GNN, and reinforcement learning models have significantly improved routing performance in WSNs. These models enable intelligent decision-making by learning complex patterns from network data, allowing for adaptive and predictive routing strategies. Among these, CDCNN and temporal convolutional models stand out due to their ability to capture long-range dependencies in sequential data, making them highly suitable for mobility prediction in mobile WSNs.

Mobility prediction has emerged as a crucial component in modern routing protocols. By accurately forecasting node movement, routing paths can be proactively adjusted, reducing link failures, minimizing packet loss, and improving overall network reliability. Studies integrating LSTM, RNN, and CDCNN models have demonstrated substantial improvements in routing stability and delay reduction.

Optimization techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf

Optimization (GWO), and NSGA-II have further enhanced routing efficiency. These methods help in selecting optimal paths, balancing energy consumption, and achieving multi-objective optimization, including trade-offs between energy, delay, and throughput. Hybrid approaches that combine deep learning with optimization algorithms have shown superior performance compared to standalone methods.

Reinforcement learning-based approaches, including Q-learning and Deep Q-Networks (DQN), have also gained prominence due to their ability to adapt to dynamic network conditions. These models continuously learn from the environment and optimize routing policies in real time, making them suitable for highly dynamic mobile WSN scenarios.

Despite these advancements, several challenges remain. One of the primary concerns is the computational complexity of deep learning models, which may not be suitable for resource-constrained sensor nodes. Additionally, scalability issues arise when deploying these models in large-scale networks. Real-time implementation and energy overhead associated with model training and inference are also critical challenges that need to be addressed.

Future research should focus on developing lightweight deep learning models that can operate efficiently on low-power devices. Edge computing and distributed learning approaches can be explored to reduce computational burden. Furthermore, cross-layer optimization techniques that integrate multiple network layers can enhance overall system performance.

In conclusion, deep learning and optimization approaches, particularly CDCNN-based models combined with mobility prediction, offer a promising direction for achieving energy-efficient and delay-sensitive routing in mobile WSNs. Continued research in this area will be essential for enabling intelligent, scalable, and sustainable WSN deployments in future IoT ecosystems.

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