Advances in Energy-Efficient Traffic Management for Wireless Sensor Networks

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Abstract:

Wireless Sensor Networks (WSNs) are widely used in applications such as environmental monitoring, healthcare, and security. However, sensor nodes suffer from limited energy, bandwidth, and processing capabilities, leading to congestion, packet loss, and reduced network lifetime. This paper reviews recent energy-efficient and congestion control techniques in WSNs, including machine learning-based routing, clustering, and optimization approaches. The study identifies limitations such as lack of adaptability, high computational complexity, and dependence on static configurations. It highlights the need for scalable, adaptive, and energy-efficient traffic management frameworks to improve performance in dynamic WSN environments.

Keywords — **Routing, Clustering, Energy Efficiency, Congestion Control, QoS.**

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are widely used in applications such as infrastructure security, military surveillance, environmental monitoring, and healthcare. These networks consist of a large number of sensor nodes deployed in an ad hoc manner to monitor physical or environmental conditions.

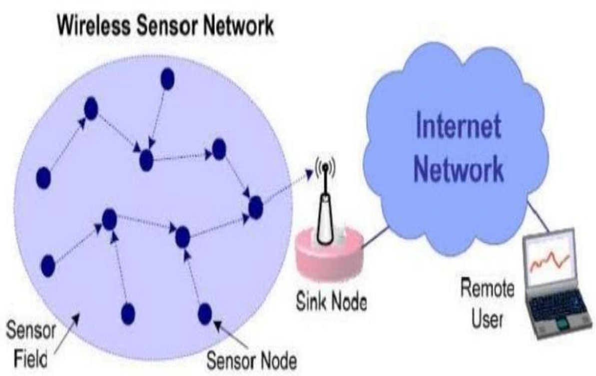

Fig.1: Basic Architecture of Wireless Sensor Network

However, WSNs face several challenges due to the limited energy, bandwidth, and storage capacity of sensor nodes. One of the major issues is traffic congestion, particularly near sink nodes, which reduces network performance by increasing packet loss, delay, and energy consumption. To address this issue, various congestion control techniques have been proposed, including rate adjustment, load balancing, and buffer management. These methods aim to improve network performance and extend network lifetime. Routing plays a critical role in WSNs by determining the path followed by data packets from the source to the destination. Efficient routing ensures reliable and energy-efficient communication.

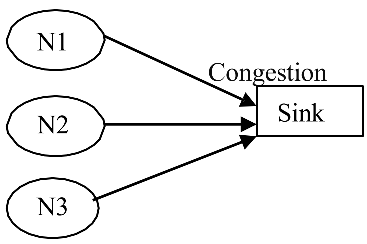

Fig.2: Traffic Congestion near Sink Node

II. LITERATURE SURVEY

Surenther et al. (2024) [1] proposed a machine learning-based energy optimization approach (ML-EOA) that combines data aggregation, artificial neural networks, and fuzzy logic. This method improves scalability and reliability but depends on fixed parameters, limiting adaptability. Akram et al. (2025) [2] introduced an energy-efficient machine learning-based clustering and routing model (EEMLCR) using Q-learning and K-means. Sahoo et al. [3] applied Multi-Criteria Decision-Making (MCDM) and smart clustering for optimal cluster head selection and energy use. The method improved performance over LEACH and fuzzy models but was less flexible in large, dynamic WSNs. Ramu et al. [4] used deep learning for harmful node detection, achieving higher throughput and lower packet loss, but ignored adaptive energy management.

Sedhuramalingam et al. (2024) [5] proposed a deep learning-based intrusion detection system with high accuracy but high energy consumption. Hu et al. (2024) [6] presented a Deep Reinforcement Learning (DRL)-based routing scheme that improved energy efficiency and security by 30% and 20%, respectively. Alsalmi et al. (2024) [7] achieved significant energy reduction using DRL-based routing but lacked adaptive clustering. Abose et al. (2024) [8] proposed clustering algorithms improving lifetime but using static thresholds. Janarthanan et al. (2024) [9] used graph neural networks for routing, improving QoS but requiring high computation. Sivakumar et al. (2024) [10, 11] focused on energy scheduling but did not address congestion control.

Shekar et al. [12, 13] applied reinforcement learning (LbREB, LbEER) for adaptive routing, achieving 48% longer lifetime and 26% lower energy use. Khatami et al. [14] combined fuzzy logic and DRL with LSTM, improving secure communication but increasing computational cost. Siamantas et al. [15] introduced T-LEACH SAS. Shwetha et al. [17] used Gaussian Mixture Clustering and an energy-efficient routing model achieving 97% PDR but fixed clustering limited flexibility.

Tewelgne et al. [18] proposed a genetic algorithm-based multi-hop protocol improving energy efficiency by 5.5% but with high complexity. Onyema et al. [19] introduced an MCDM-based secure routing protocol (MLSRP) with 98% accuracy but limited adaptability to dynamic traffic. Chandan et al. [20] proposed a hybrid machine learning and cryptographic protocol achieving 97% throughput and 94% low delay, but real-time congestion control was not included.

TABLE 2.1Summary of Existing Energy Optimization Techniques in WSNs

Author/ Year	**Dataset/ Domain**	**Method/Technique**	**Limitations**	**Findings**
Surenther et al. (2024)	WSN	ML-EOA (ANN + Fuzzy)	Fixed parameters	Improved scalability & reliability
Pujitha et al. (2025)	WSN	ECBMR routing	No congestion control	92% PDR
Shin et al. (2025)	WSN	Sink location service	No real-time adaptation	29% energy saving
Shekar et al. (2025)	WSN	RL-based routing (LbREB, LbEER)	Limited traffic handling	48% longer lifetime
Khatami et al. (2025)	WSN	FDRL + LSTM	High complexity	Improved security & efficiency
Siamantas et al. (2025)	WSN	T-LEACH protocol	Static scheduling	Energy-efficient routing
Vishwas et al. (2025)	WSN	Survey-based study	No implementation	General insights
Shwetha et al. (2025)	WSN	GMCML routing	Fixed clustering	97% PDR
Tewelgne et al. (2025)	WSN	GA-based clustering	High complexity	Improved lifetime
Onyema et al. (2025)	WSN	MLSRP (ML-based routing)	Low adaptability	98% accuracy
Chandan et al. (2025)	WSN	ML + Cryptographic protocol	No congestion focus	High throughput & low delay

TABLE 2.2: Summary of Energy-Efficient Traffic Management in WSNs

Author/ Year	**Dataset/ Domain**	**Method/Technique**	**Limitations**	**Findings**
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III. METHODOLOGY

The proposed methodology introduces a multi-layer energy-efficient and congestion-aware traffic management framework for Wireless Sensor Networks (WSNs). The design focuses on optimizing energy consumption, reducing congestion, and improving overall network lifetime through adaptive and intelligent mechanisms.

A. System Architecture:

The framework is organized into five functional layers:

1) Sensing Layer:

Sensor nodes are deployed randomly to monitor environmental conditions such as temperature, humidity, or motion. Each node periodically senses data and forwards it to the upper layers.

2) Clustering Layer:

Nodes are grouped into clusters to minimize communication overhead. Cluster Head (CH) selection is based on residual energy, node proximity, and communication cost. A dynamic clustering approach is used to balance energy consumption across the network.

3) Energy-Aware Routing Layer:

Data is transmitted from cluster members to the sink node through optimized routes. Routing decisions consider remaining energy of nodes, distance to sink, and link quality. Multi-hop communication is adopted to reduce long-distance transmissions and conserve energy.

4) Congestion Detection Layer:

Congestion is identified using real-time network parameters such as buffer occupancy, packet arrival rate, and queue length. When congestion is detected, the system triggers adaptive control mechanisms to prevent packet loss and delays.

5) Traffic Management Layer:

This layer ensures smooth data transmission using rate control (adjusts packet transmission rate dynamically), load balancing (distributes traffic across multiple paths), and queue management (prioritizes critical data packets).

B. Working Procedure:

The overall workflow of the proposed system is as follows: Sensor nodes collect environmental data continuously. Nodes are organized into clusters using energy-aware clustering. Cluster Heads aggregate data to reduce redundancy. Data is routed to the sink using optimized multi-hop paths.

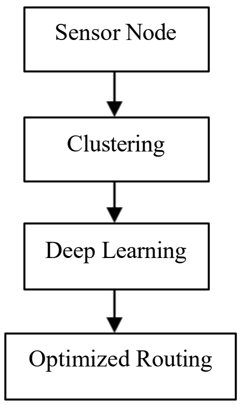

Fig.3: Future Energy-Efficient Framework

Congestion is monitored at each node using buffer and traffic metrics. If congestion occurs, the transmission rate is reduced and alternative routes are selected. Energy levels are continuously monitored to update clustering and routing decisions dynamically.

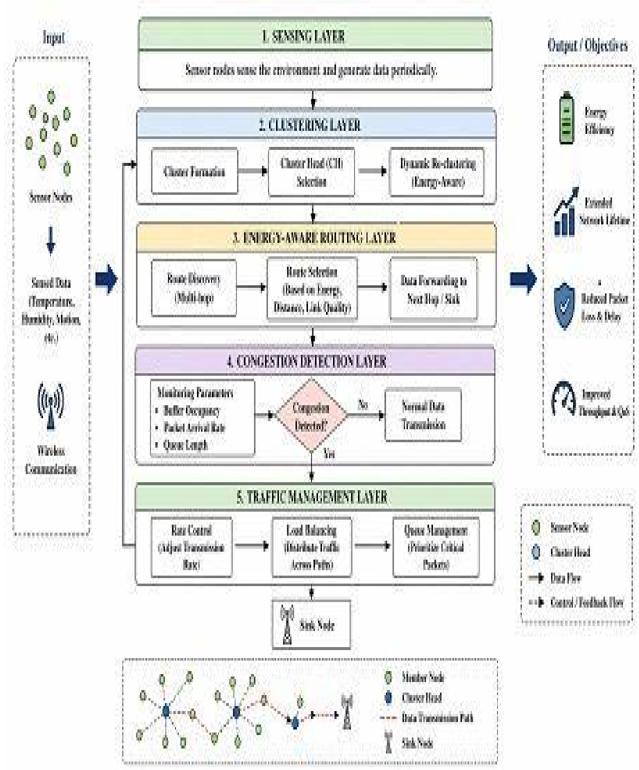

Fig.4 Proposed methodology for energy efficient congestion aware traffic management in WSNs

IV. RESULTS AND DISCUSSION

The comparative analysis of existing techniques highlights that machine learning and deep learning-based approaches outperform traditional clustering methods in terms of energy efficiency and network lifetime. Techniques such as DRL-based routing and hybrid models achieve significant improvements in throughput and delay reduction.

However, these methods introduce higher computational complexity and may not be suitable for resource-constrained WSNs. Static clustering approaches are simple but fail to adapt to dynamic network conditions. Therefore, a trade-off exists between performance and complexity.

V. RESEARCH GAP OF EXISTING WORK

Despite numerous innovations, most studies focus on isolated parameters like energy or security rather than holistic traffic management. Many rely on static clustering or computationally heavy models unsuited to real-time adaptation. Current WSNs demand scalable, energy-efficient, and adaptive frameworks capable of balancing traffic and energy dynamically with minimal overhead.

VI. CONCLUSIONS

This survey reviewed energy-efficient and congestion-aware schemes in WSNs, highlighting key strengths and weaknesses of machine learning, optimization, and clustering-based approaches. Although these methods enhance lifetime and reliability, they often lack adaptability and computational feasibility for real-world large-scale WSNs. Future research should focus on hybrid models combining deep learning with adaptive clustering and lightweight optimization to achieve sustainable, real-time congestion control in dynamic environments.

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