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Energy-Efficient and QoS-Aware Traffic Management in Wireless Sensor Networks Using Deep Learning and Multi-Objective Optimization

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ABSTRACT

Wireless Sensor Networks (WSNs) are widely used in applications such as environmental monitoring, industrial automation, and smart cities. However, limited energy resources and Quality of Service (QoS) requirements remain critical challenges. This paper proposes an integrated framework for energy-efficient and QoS-aware traffic management using deep learning and multi-objective optimization. The framework combines Graph Neural Networks (GNNs) for traffic prediction, Reinforcement Learning (RL) for adaptive routing, and a Deep Learning-based Clustering Model (DL-CM) for cluster head selection. Simulation and hardware-based evaluations demonstrate significant improvements in energy consumption, network lifetime, packet delivery ratio, and latency compared to conventional protocols such as LEACH and HEED. The proposed model provides a scalable and intelligent solution for next-generation WSNs.

Introduction

Wireless Sensor Networks (WSNs) are a key component of the Internet of Things (IoT), enabling real-time monitoring in diverse environments. These networks consist of battery-powered sensor nodes with limited computational and energy resources. Efficient energy management is essential to prolong network lifetime. Traditional approaches such as LEACH and HEED focus on clustering and duty cycling to conserve energy. However, they often fail to address QoS requirements like latency, reliability, and scalability. Recent advancements in machine learning provide opportunities to improve network intelligence and adaptability. This study introduces a unified framework that integrates deep learning, clustering, and multi-objective optimization to enhance both energy efficiency and QoS performance in WSNs.

Problem Statement:

WSNs face several challenges due to limited energy, dynamic network conditions, and scalability requirements. Traditional routing protocols suffer from uneven energy consumption, inefficient cluster head selection, and lack of QoS awareness. Cluster heads (CHs) play a critical role in data aggregation and communication. Poor CH selection leads to rapid energy depletion and network instability. Additionally, factors such as node mobility, traffic variation, and link quality fluctuations complicate routing decisions. The objective of this work is to design an intelligent framework that minimizes energy consumption while maximizing network lifetime, packet delivery ratio, and communication reliability using deep learning techniques.

Contributions:

1. Proposes an integrated traffic management framework combining deep learning and optimization.
2. Develops a Deep Learning-based Clustering Model (DL-CM) for efficient CH selection.
3. Introduces a GNN-based traffic prediction model for congestion control.
4. Implements multi-objective routing optimization considering energy, delay, and reliability.
5. Incorporates cross-layer optimization across physical, MAC, and network layers.
6. Supports mobility-aware communication and adaptive routing.
7. Integrates security mechanisms using trust-based routing.
8. Validates performance through simulations and hardware experiments.

Related Work:

Energy-efficient routing in WSNs has been widely studied using clustering protocols such as LEACH and HEED. While effective in reducing energy consumption, these approaches lack scalability and QoS support.Machine learning techniques, including deep learning and reinforcement learning, have recently been applied for traffic prediction and routing optimization. These methods improve adaptability but often focus on single objectives. Mobility-aware routing and UAV-assisted data collection have also been explored. However, most existing works do not integrate energy efficiency, QoS, mobility, and security into a unified framework, highlighting a significant research gap.

Energy Consumption Model: The first-order radio energy model is used to estimate transmission and reception energy.

Transmission energy is given by: $E\_tx(k, d) = E\_elec \times k + E\_amp \times k \times d^2$ 1

Reception energy is given by: $E\_rx(k) = E\_elec \times k$ 2

Where k is the packet size, d is the transmission distance, E_elec is the electronic energy consumption per bit, and E_amp is the amplifier energy coefficient.

Cluster Head Selection Function: In the proposed DL-CM model, cluster head selection is formulated as an optimization problem. The cluster head selection score for node i is:

$$CH\_i = w_1 \times (E\_i / E\_max) + w_2 \times (1 / d\_iS) + w_3 \times LQ\_i + w_4 \times C\_i \quad 3$$

Where E_i is the residual energy, di_S is the distance to the sink, LQ_i is the link quality, C_i is the node centrality, and w_1, w_2, w_3, and w_4 are weighting coefficients. The node with the highest cluster head score is selected as the cluster head.

Multi-Objective Optimization Function: The objective of the DL-CM model is to minimize overall network cost: $Min\ F = \alpha\, E\_total + \beta\, D\_avg + \gamma\, L\_delay$ 4

Where E_total is the total energy consumption, D_avg is the average transmission distance, L_delay is the end-to-end delay, and α, β, γ are weighting parameters.

Deep Learning Model: **The DL-CM model combines GNN**, **captures spatial relationships and RNN/LSTM captures temporal traffic patterns**

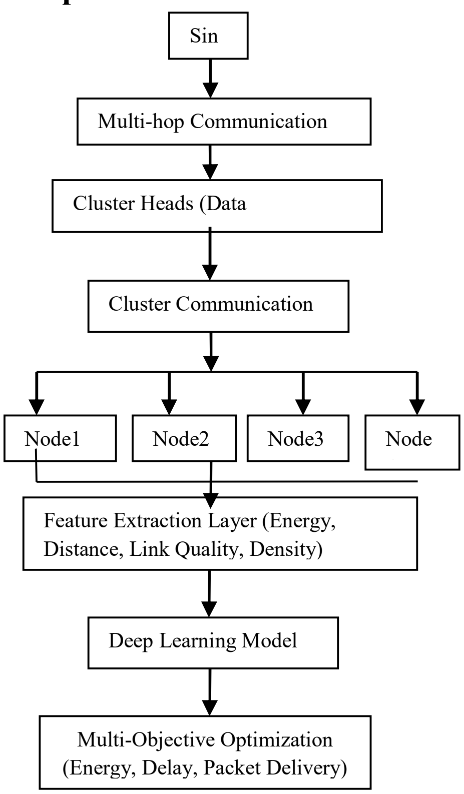
Node feature vector: $\boldsymbol{Xi = [Ei, di, LQi, Ci, Ni]X\_i}$

Cluster head probability $P(CHi) = Softmax(Wohi)P(CH\_i)$ **5**

Network Model: **A WSN with N nodes is considered where nodes are clustered and communicate with the sink via multi-hop routing. Optimization focuses on minimizing energy while maintaining QoS.**

Security Mechanism: Trust-based routing prevents malicious nodes from becoming cluster heads. Intrusion detection identifies abnormal traffic patterns.

Proposed Framework:



System Architecture

The proposed frame work integrates deep-learning -based traffic prediction with adaptive Clustering and multi-objective routing Optimization. Sensor nodes collect environmental data and transmit it to cluster heads, which aggregate and forward the information to the sink node. A Deep learning model analyzes network Parameter such as residual energy, node density and link quality to optimize Cluster head selection and routing decision.

Comparison of Existing WSN Routing Protocols:

Several routing and clustering protocols have been proposed to improve energy efficiency and network lifetime in WSNs. However, many suffer from poor scalability, lack of QoS support, and inability to adapt to dynamic conditions. Table 1 presents a comparison of commonly used routing protocols with the proposed DL-CM framework.

Table 1: Comparison of WSN Routing Protocols

Protocol	Type	Energy Efficiency	Scalability	QoS Support	Mobility	Limitation
LEACH	Cluster-based	Medium	Low	Low	No	Random CH selection
HEED	Cluster-based	Medium	Medium	Low	No	Iterative overhead
PEGASIS	Chain-based	High	Low	Low	No	Large comm. delay
TEEN	Cluster-based	High	Low	Medium	No	Time-critical only
APTEEN	Hybrid	Medium	Medium	Medium	No	High complexity
DEEC	Heterogeneous clustering	High	Medium	Medium	No	Energy imbalance
DDEEC	Enhanced DEEC	High	Medium	Medium	No	Limited scalability
SEP	Stable election	Medium	Medium	Low	No	Not topology-adaptive
GEAR	Geographic routing	Medium	High	Medium	Yes	Needs location info
Proposed DL-CM	Deep learning clustering	Very High	High	High	Yes	Computational overhead

Simulation Environment: Experiments were conducted using a large-scale WSN simulation environment. Table 2 summarizes the simulation parameters. Baseline protocols used for comparison include LEACH, HEED, and Energy-Aware Routing (EAR).

***Table 2**: Simulation Parameters*

Parameter	Value
Network Area	1000 m × 1000 m
Number of Nodes	100–1000
Communication Range	100 m
Initial Energy	2 Joules
Simulation Time	5,000 rounds
Packet Size	512 bytes

Hardware Testbed

A small-scale experimental deployment was also conducted using physical sensor platforms. Hardware platforms used include TelosB sensor nodes, MicaZ sensor nodes, and Raspberry Pi-based IoT nodes. Nodes were deployed across a laboratory environment simulating real-world interference and synchronization challenges.

Research Gap

Existing WSN routing and clustering protocols like LEACH and HEED mainly focus on energy efficiency but often neglect QoS factors such as latency, reliability, scalability, and load balancing. Recent machine learning approaches improve specific aspects like routing or traffic prediction, yet they typically address only single objectives. Moreover, integration of adaptive clustering, cross-layer optimization, mobility awareness, security, and real-time prediction is limited. Therefore, a unified framework combining deep learning, multi-objective optimization, and adaptive communication strategies is still needed to enhance both energy efficiency and QoS in WSNs.

Energy Consumption: The proposed framework achieved a 28% reduction in overall energy consumption compared to LEACH and a 19% reduction compared to HEED, primarily due to the integration of predictive traffic management and adaptive clustering mechanisms. Figure 1 presents the energy consumption comparison across protocols.

Network Lifetime: The proposed framework extends network lifetime by ensuring balanced energy dissipation across sensor nodes, thereby preventing premature node failures. Table 3 compares network lifetime across protocols. Figures 2 and 3 illustrate the network survival curves.

Packet Delivery Ratio: The GNN-based traffic prediction improved congestion management, resulting in higher packet delivery ratios. Table 3 presents packet delivery ratio results. Figures 4 through 7 illustrate packet delivery performance under varying network conditions.

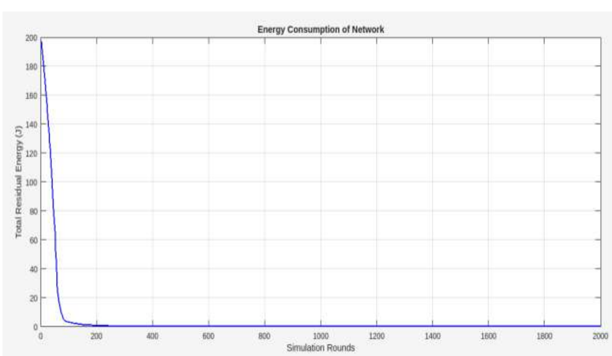
***Table 3**: Network Life time and Packet Delivery Ratio Comparison*

	Network Lifetime	Packet Delivery Ratio
LEACH	3100 Rounds	88
HEAD	3500 Rounds	91
DL-CM MODELLING	4200 Rounds	96

Latency and Jitter: The proposed multi-objective routing strategy reduced end-to-end delay by approximately 23% and jitter by 17% compared to baseline protocols.

***Figure 1**: Energy Consumption Comparison Across Protocols*

***Figure 2:** Network Lifetime Comparison — Node Survival Over Rounds*



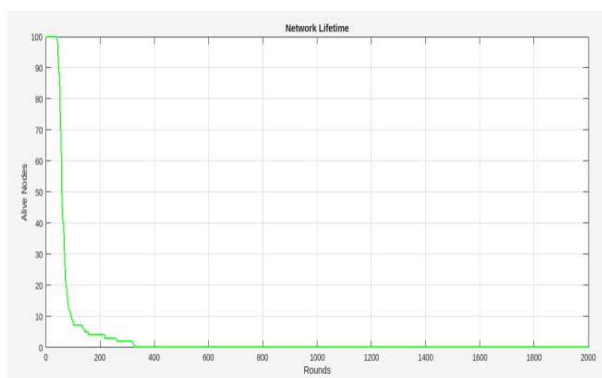
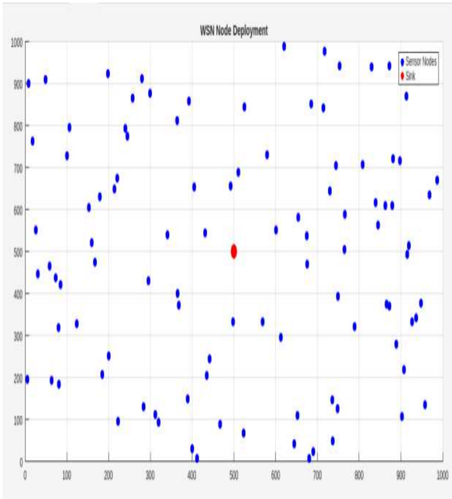


***Figure 3:** Cumulative Energy Dissipation*

*Figure **4:** Packet Delivery Ratio vs. Number of Rounds over Simulation Rounds*



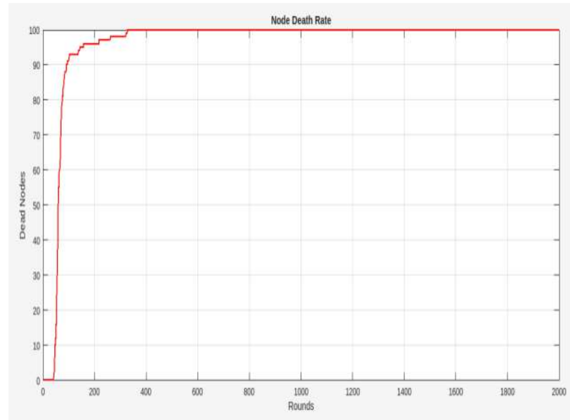
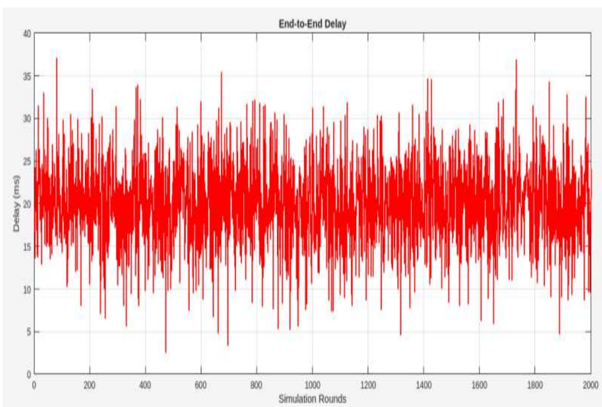
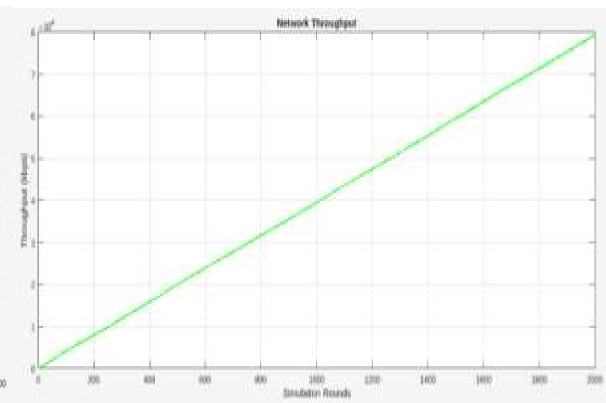


Figure 5: *Packet Delivery Ratio vs. Node Density* ***Figure 6:*** *Throughput Comparison*

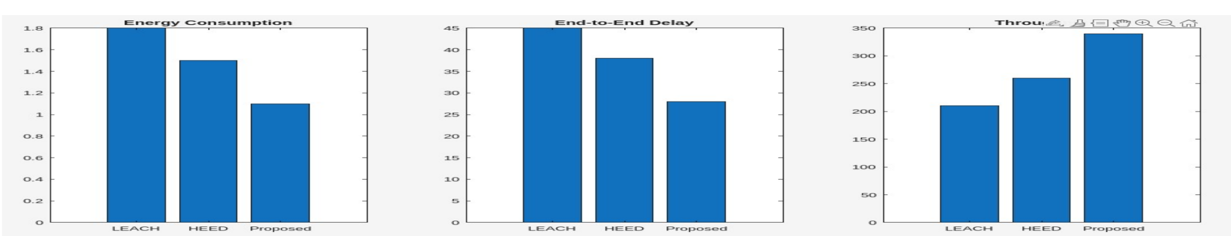




Scalability Analysis

Simulation results with up to 1,000 nodes demonstrate stable operation with limited overhead. The hybrid centralized–distributed architecture further enhances scalability in ultra-dense network scenarios. Figure 8 presents the scalability analysis.

***Figure** 7: Scalability Analysis: Energy Consumption vs. Network Size*



Note. Average energy consumption per node as the number of deployed nodes increases from 100 to 1,000.

Discussion

Experimental findings indicate that combining deep learning models with adaptive clustering and multi-objective routing considerably enhances the performance of WSNs. Mobility-aware techniques further improve adaptability in dynamic environments such as UAV-assisted monitoring systems. Additionally, cross-layer optimization and energy harvesting mechanisms prolong network lifetime and enhance sustainability.

Future Work: Future research will focus onReal-world smart city deployments, Energy harvesting integration, Federated learning for decentralized training ,6G-enabled IoT systems and Advanced reinforcement learning for mobile sinks

Conclusion:

This paper presents an intelligent framework for energy-efficient and QoS-aware traffic management in WSNs. By combining deep learning, adaptive clustering, and multi-objective optimization, the proposed model significantly improves energy efficiency, network lifetime, and reliability. The DL-CM model provides a scalable and effective solution for next-generation WSN applications, addressing key limitations of traditional protocols.

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