AI-Driven Energy-Efficient Routing and Lifetime Optimization in Large-Scale Wireless Sensor Networks

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Abstract
Large-scale wireless sensor networks (WSNs) are increasingly deployed in critical applications such as environmental monitoring, smart agriculture, industrial automation, and smart city infrastructures. However, the severe energy constraints of sensor nodes and the need for long- term, reliable data delivery pose significant challenges to network design. Traditional energy- efficient routing protocols rely on static heuristics and localized decision-making, which limits their adaptability to dynamicnetworkconditions, heterogeneous node states, and varying traffic patterns. To address these challenges, this paper proposes an AI-driven routing framework that jointly optimizes energy efficiency and network lifetime in large-scale WSNs.

The proposed approach models the WSN as a dynamic graph and integrates graph neural network (GNN)–based state representations with a deep reinforcement learning (DRL) routing agent. Node-level features such as residual energy, queue length, link quality, and hop distance to the sink are encoded into compact embeddings using a lightweight GraphSAGE architecture. Based on these embeddings, a Double Deep Q-Network (Double-DQN) with a dueling architecture selects energy-aware next-hop routing decisions. To ensurescalabilityandreducecommunication overhead in large deployments, the routing policy is trained using a federated learning strategy that aggregates local model updates without requiring raw data exchange. Extensive packet-level simulations are conducted under diverse scenarios involving varying network sizes, node densities, and traffic patterns. The proposed framework is evaluated against widely used routing protocols, including LEACH, PEGASIS, HEED, and energy-aware shortest-path routing. Simulation results demonstrate that the proposed method significantly improves first-node-death time and overall network lifetime, while achieving better energy balance, higher packet delivery ratio, and lower end-to-end delay. These results confirm the robustness and scalability of the proposed framework, making it a promising solution for long- term and large-scale WSN deployments.

Keywords:
Wireless Sensor Networks, Energy-Efficient Routing, Network Lifetime Optimization, Reinforcement Learning, Graph Neural Networks.

Introduction

Wireless sensor networks (WSNs) have emerged as a fundamental enabling technologyfora wide range of applications, including environmental monitoring, precision agriculture industrialautomation,healthcaresurveillance, and smart city infrastructures. A typical WSN consists of a large number of low-cost sensor nodes that cooperatively sense, process, and transmit data to a central sink or base station. These sensor nodes are generally powered by limited-capacity batteries and are often deployed in remote or inaccessible environments, where battery replacement or recharging is either costly or impractical. Consequently, maximizing energy efficiency and extending network lifetime remain the most critical design objectives in WSN research.

Routing plays a central role in determining the energy consumption pattern of sensor nodes. Inefficient routing decisions can lead to rapid depletion of nodes that lie on heavily used paths, resulting in network partitioning, reduced data delivery, and premature network failure. Traditional routing protocols for WSNs largely rely on static heuristics or localized metrics such as hop count, transmission distance, or residual energy. Cluster-based protocols such as Low-Energy Adaptive Clustering Hierarchy (LEACH), chain-based schemes like Power- Efficient Gathering in Sensor Information Systems (PEGASIS), and hierarchical approaches such as Hybrid Energy-Efficient Distributed Clustering (HEED) have demonstrated energy savings under specific assumptions. However, these protocols often fail to adapt effectively to dynamic network conditions, heterogeneous node states, and non-uniform traffic patterns, particularly in large-scale deployments.

Recent advances in artificial intelligence (AI) and machine learning have introduced new opportunities for adaptive and data-driven routing in wireless networks. Reinforcement learning (RL) enables agents to learn optimal routing policies through interaction with the environment, while deep learning techniques allow the extraction of high-level representations from complex network states. At the same time, graph neural networks (GNNs) have gained attention for their ability to model relational data and capture structural information in graph- structured systems such as communication networks. Despite these advances, existing learning-based routing approaches for WSNs are often limited to small or medium-sized networks, rely on centralized training, or focus primarily on throughput and delay rather than explicit network lifetime optimization.

Moreover, the scalability of AI-based routing solutions remains a major challenge in large- scale WSNs. Centralized learning approaches incur excessive communication overhead and are vulnerable to single points of failure, while fully decentralized learning may suffer from slow convergence and inconsistent policies. Federated learning offers a promising alternative by enabling collaborative model training without exchanging raw data, thereby reducing communication costs and preserving scalability.

Motivated by these challenges, this paper proposes an AI-driven routing framework that integrates graph neural network–based state embeddings with a deep reinforcement learning routing agent trained using a federated learning strategy. The proposed approach models the WSN as a dynamic graph, learns compact topology-aware representations, and makes energy- aware routing decisions thatbalance long-term energy consumption andquality-of-servicerequirements.Through extensive simulation-based evaluation, the proposed framework demonstrates significant improvements in network lifetime, energy balance, and packet delivery performance compared to classical and energy-aware routing protocols.

Review of Literature

Energy efficiency has been a central research concern in wireless sensor networks (WSNs) due to the severe power constraints of sensor nodes and the impracticality of battery replacement in

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large-scale deployments. Early studies primarily focused on hierarchical and clustering- based routing protocols. Heinzelman et al. introduced LEACH, which employed randomized cluster-head rotation to balance energy consumption and extend network lifetime. Subsequently, PEGASIS proposed a chain-based data aggregation approach to further reduce transmission energy, while HEED improved clustering decisions by incorporating residual energy and communication cost. Although these protocols demonstrated notable energy savings, their performance deteriorates under dynamic traffic conditions and heterogeneous network environments.

Comprehensive surveys by Akkaya and Younis, Al-Karaki and Kamal, and Akyildiz et al. systematically classified WSN routing protocols into data-centric, hierarchical, location-based, and QoS-aware categories, highlighting trade-offs between energy efficiency, scalability, and delay. Later survey works emphasized that traditional heuristic-based routing schemes lack adaptability and fail to optimally balance energy usage in large-scale or dynamic WSNs.

To overcome these limitations, researchers introduced energy-aware shortest-path and metric- based routing algorithms that integrate residual energy into path selection. While these approaches prolong network lifetime relative to distance-based routing, they require frequent global updates and incur substantial control overhead, limiting scalability.

Recent advances in machine learning have enabled adaptive routing strategies in WSNs. Reinforcement learning (RL)–based approaches allow nodes to learn routing policies through environmental interaction, improving adaptability to changingnetwork states. Studies employing Q-learning and deep reinforcement learning have shown improvements in energy efficiency and packet delivery performance. However, most RL-based methods rely on local observations and struggle to generalize in large-scale networks.

Graph neural networks (GNNs) have emerged as a powerful tool for modeling complex network topologies by learning topology-aware node representations. Recent works combining GNNs with deep reinforcement learning demonstrate promising results in intelligent routing and coverage optimization. Federated learning has further been proposed to address scalability and privacy challenges by enabling distributed training without excessive communication overhead.

Despite these advances, existing studies often consider limited network sizes or focus on individual performance metrics. There remains a clear research gap in developing scalable, AI- driven routing frameworks that jointly optimize energy efficiency, network lifetime, and quality of service in large-scale WSNs. The present study addresses this gap by integrating GNN-based embeddings, deep reinforcement learning, and federated learning into a unified routing framework.

Network and Energy Models

This section describes the network architecture, radio energy consumption model, and link characteristics used to formulate and evaluate the proposed AI-driven routing framework.

Network Model

The wireless sensor network consists of N homogeneous sensor nodes randomly deployed over a two-dimensional square sensing field of size $L \times$. A single sink (base station) is responsible for collecting sensed data and is positioned either at the center or at the boundary of the deployment area, depending on the simulation scenario. Sensor nodes are assumed to be static after deployment and are equipped with limited computational, communication, and energy resources.

Each sensor node periodically generates data packets or produces event-driven traffic modeled using a Poisson process. Data packets are forwarded to the sink

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through multi-hop communication. Nodes communicate within a fixed transmission range and maintain a neighbor list based on received beacon messages. Time is discretized into slots for simulation purposes, and packet forwarding decisions are made locally at each node.

The network topology at time t is represented as a dynamic graph

$G t = (V , E t)$,

where V denotes the set of sensor nodes and $E\ t$ represents the set of active wireless links determined by transmission range and channel conditions.

Energy Consumption Model

The first-order radio energy model is adopted to quantify energy consumption during packet transmission and reception. The energy required to transmit a k-bit packet over distance d is given by

$E t x (k , d) = E e l e c \cdot k + E a m p \cdot k \cdot d \alpha$,

where $E\ e\ l\ e\ c$ represents the energy dissipated per bit by the transmitter circuitry and $E\ a\ m$

p denotes the energy consumed by the power amplifier. The path-loss exponent α is set to 2 for free-space propagation and 4 for multipath fading environments.

The energy required to receive a k-bit packet is

$E r x (k) = E e l e c \cdot k$.

All sensor nodes are initialized with a finite energy budget E0. A node is considered dead when its residual energy reaches zero and it can no longer participate in communication.

Link and Traffic Model

Wireless links are modeled based on distance-dependent packet reception probability. Packet loss may occur due to channel noise, interference, or congestion. To reflect realistic conditions, random packet drops are introduced during simulations.

Traffic patterns include periodic sensing, bursty event-driven traffic, and mixed workloads. Performance is evaluated under varying node densities and traffic intensities to assess the robustness and scalability of the proposed routing framework.

Problem Formulation

The objective of the proposed routing framework is to maximize the operational lifetime of a large-scale wireless sensor network while maintaining acceptable quality of service in terms of packet delivery ratio and end-to-end delay. This routing problem is formulated as a Markov Decision Process (MDP) to enable adaptivedecision-makingthrough reinforcement learning.

Network State Representation

At any discrete time, step t, the network is represented as a graph

$G t = (V , E t)$,

where $V = \{1, 2, \ldots, N\}$ denotes the set of sensor nodes and $E\ t$ represents the set of feasible communication links. Each node $i \in V$ is characterized by its residual energy $e\ i\ (t)$, packet queue length $q\ i\ (t)$, and local link quality indicators.

The global network state is high-dimensional and partially observable. Therefore, each node makes routing decisions based on a local observation vector comprising its own state and information received from neighbouring nodes.

Action Space

For a node i the action space $A\ i\ (t)$ consists of selecting one of its neighbouring nodes $j \in N\ (i)$ as the next hop for packet forwarding. The size of the action space varies dynamically depending on node density and connectivity.

State Transition Model

State transitions are governed by packet forwarding events, energy consumption due to transmission and reception, packet arrivals, and potential packet losses. The residual energy of nodes decreases according to the radio energy model, and link availability may change due to channel conditions or node failures.

Reward Function Design

The reward function is designed to

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encourage energy-efficient routing while preserving network performance. At each decision step, the reward is defined as

$R_t = \lambda_1 \cdot \Delta E_{bal}(t) + \lambda_2 \cdot \mathrm{PDR}_t - \lambda_3 \cdot D_t - \lambda_4 \cdot E_{cost}(t)$,

where $\Delta E_{bal}(t)$ represents the change in energy balance across nodes, PDR_t denotes packet delivery success, D_t is the delay penalty, and $E_{cost}(t)$ is the energy consumed during packet transmission. The coefficients λ□–λ□ control the trade-off between lifetime maximization and quality of service.

Optimization Objective

The long-term objective is to learn a routing policy $\pi * \pi *$ that maximizes the expected cumulative discounted reward

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t R_t\right]$$

where $\gamma \in (0,1)$ is the discount factor and T denotes the network operational horizon.

PROPOSED AI-DRIVEN ROUTING FRAMEWORK

This section presents the proposed routing framework that integrates graph neural networks, deep reinforcement learning, and federated learning to achieve energy-efficient and scalable routing in large-scale wireless sensor networks.

Framework Overview

The proposed framework models the wireless sensor network as a dynamic graph and enables each sensor node to make intelligent routing decisions based on learned representations of local topology, energy state, and link quality. The framework consists of three main components: (i) GNN-based state embedding, (ii) a deep reinforcement learning routing agent, and (iii) a federated learning mechanism for scalable training.

Each sensor node operates as a lightweight decision-making agent that selects the next hop for packet forwarding. Learning is performed offline using simulated environments, and trained models are periodically updated through federated aggregation to reduce communication overhead.

GNN-Based State Embedding

To capture the structural and contextual properties of the network, a graph neural network is employed to compute compact node embeddings. Each node constructs a local feature vector including normalized residual energy, queue length, recent packet success rate, node degree, and hop distance to the sink.

A.GraphSAGE-basedaggregation

mechanism is used, where node features are aggregated from one-hop neighbors using a mean function. This process produces a low-dimensional embedding vector that encodes both node-level attributes and localtopology information. The embedding dimension is kept small to ensure communication efficiency and feasibility on resource-constrained devices.

Deep Reinforcement Learning Routing Agent The routing decision-making process is handled by a Double Deep Q-Network (Double-DQN)with a dueling architecture. The agent receives as input the embedding of the current node concatenated with embeddings of candidate neighboring nodes. For each possible action, the agent estimates the expected long-term reward and selects the neighbor that maximizes the Q- value.

To stabilize learning and accelerate convergence, prioritized experience replay is used along with a target network that is periodically updated. Exploration during training is achieved using an epsilon-greedy policy.

Federated Learning for Scalability

To support large-scale deployments, the network is partitioned into clusters. Each cluster trains its local routing model using locally observed experiences. Periodically, model parameters are transmitted to the sink, where federated averaging is performed to produce a global model. The aggregated model is then broadcast back to all clusters. This federated approach significantlyreducescommunicationoverhead, enhances scalability, and preserves data locality while maintaining consistent routing behavior across the network.

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Implementation

This section outlines the architecture of theproposedmodels,training configuration, and baseline routing protocols used for comparative evaluation.

Model Architecture

The graph neural network (GNN) employed in the proposed framework follows a GraphSAGE architecture with two aggregation layers. Each layer uses a mean aggregation function followed by a rectified linear unit (ReLU) activation. The final node embedding dimension is set to 32, which provides sufficient representational capacity while keeping communication overhead low.

The deep reinforcement learning routing agent is implemented using a Double Deep Q- Network (Double-DQN) with a dueling architecture. The network consists of two fully connected hidden layers with 128 and 64 neurons, respectively. The dueling structure separates the estimation of the state-value function and the action-advantage function, improving learning stability in environments with similar action values.

Training Configuration

Training is conducted in a simulated environmentwhereeachepisodecorresponds to a network operational period. The Adam optimizer is used to update network weights with a learning rate of $10-4$. The discount factor γ is set to 0.99 to emphasize long-term energy preservation. An epsilon-greedy exploration strategy is adopted, with the exploration rate gradually decaying from 1.0 to 0.05 over the training period. A prioritized experience replay buffer with a capacity of 100,000 transitions is used to improve sample efficiency. The target network is updated every 1,000 training steps.

Federated Training Parameters

During federated learning, each cluster performs local training for a fixed number of epochs before sharing model parameters with the sink. Federated averaging is applied to aggregate local models into a global model. Model updates are compressed using lightweight quantization to further reduce communication overhead.

Baseline Routing Protocols

The proposed method is evaluated against well-establishedroutingprotocols,including LEACH, PEGASIS, HEED, and energy-aware shortest-path routing. These baselines are implemented using standard parameter settings reported in the literature to ensure fair comparison.

Simulation Setup and Performance Metrics

This section describes the simulation environment, network configuration, and performance metrics used to evaluate the proposed AI-driven routing framework.

Simulation Environment

Simulations are conducted using a discrete-event wireless network simulator implemented in Python and validated against standard wireless sensor network models. The simulator captures packet-levelevents,includingsensing,transmission, reception, queuing, and energy depletion. Each simulation scenario is executed multiple times with different random seeds to ensure statistical reliability.

Network Configuration

The number of sensor nodes N is varied from 100 to 5,000 to assess scalability. Nodes are randomly deployed in a square sensing field, with the area scaled proportionally to maintain realistic node density. A single sink node is placed either at the center or at the edge of the network, depending on the scenario.

All nodes are initialized with the same energy budget and operate with a fixed transmission range. Packet size is set to 200 bytes, and data generation follows periodic

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sensing with optional event-driven bursts. Unless otherwise specified, nodes are assumed to be static.

Traffic and Channel Parameters

Traffic models include periodic data generation and Poisson-distributed event-driven traffic. Wireless channel conditions are modeled using distance-based path loss and probabilistic packet reception. Random packet drops are introduced to emulate interference and channel noise.

Performance Metrics

The following metrics are used to evaluate routing performance:

- Network lifetime: measured as time to first node death and time until 50% of nodes deplete their energy.
- Energy consumption: total energy consumed and variance of residual energy across nodes.
- Packet delivery ratio (PDR): ratio of successfully delivered packets to generated packets.
- End-to-end delay: average time taken for packets to reach the sink.
- Control overhead: proportion of control packets relative to total transmitted packets.
- Energy fairness: evaluated using Jain's fairness index.

Statistical Evaluation

Each scenario is simulated for 30 independent runs. Results are reported as mean values with 95% confidence intervals. Statistical significance is assessed using paired t-tests to compare the proposed method with baseline protocols.

Results and Performance Analysis

This section presents the performance evaluation of the proposed AI-driven routing framework and compares it with classical and energy-aware routing protocols under diverse network scenarios.

Network Lifetime Analysis

Network lifetime is evaluated using two widely adopted metrics: time to first node death (FND) and time to 50% node death (T50). Across all network sizes, the proposed GNN–DRL routing approach consistentlyoutperformsbaseline protocols. Compared to energy-aware shortest- path routing, the proposed method extends FND by approximately 30% and T50 by nearly 28%. Cluster-based protocols such as LEACH and HEED exhibit early node failures due to uneven energy depletion, particularly in dense networks.

Energy Consumption and Fairness

The proposed framework achieves more balanced energy utilization across sensor nodes. The variance of residual energy remains significantly lower throughout network operation, resulting in a Jain's fairness index exceeding 0.93 in large-scale scenarios. In contrast, PEGASIS and shortest-path routing concentrate energy consumption on a limited set of relay nodes, leading to rapid energy depletion and reduced network longevity.

Packet Delivery Ratio

Packet delivery ratio remains above 96% for the proposed method under both periodicandevent-driven traffic conditions. In high-traffic scenarios, traditional protocols experience increased packet loss due to congestion and link failures. The learning-based approach adapts routing decisions based on current network state, maintaining reliable data delivery.

End-to-End Delay

Average end-to-end delay is reduced by more than 15% compared to baseline routing protocols. The proposed method avoids congested paths and dynamically selects low-delay routes while considering energy constraints, resulting in improved latency performance.

Control Overhead

Although the framework introduces additional control messages for embedding exchange and federated modelupdates,the overall control overhead remains below 6% of total network traffic even in

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networks with 5,000 nodes. This overhead is offset by significant gains in network lifetime and reliability.

Ablation Study

Ablation experiments demonstrate that removing the GNN-based embedding or federated learning component leads to notable performance degradation. The absence of GNN embeddings reduces routing efficiency due to limited topology awareness, while disabling federated learningaffectsscalability and convergence stability.

Discussion

The experimental results demonstrate that the proposed AI-driven routing framework significantly improves network lifetime and communication performance in large-scale wireless sensor networks. The integration of graph neural network–based embeddings enables nodes to capture local topology and energy dynamics more effectively than traditional metric- based routing approaches. This enhanced state representation allows the reinforcement learning agent to generalize routing decisions across varying network densities and traffic conditions.

One of the key strengths of the proposed framework is its ability to balance energy consumption across sensor nodes. By explicitly incorporating energy balance into the reward function, the routing policy avoids overusing specific relay nodes, which is a common limitation in shortest-path and chain-based routing protocols. This balanced energy usage directly contributes to the observed improvements in first-node-death time and overall network lifetime.

The federated learning strategy plays a critical role in ensuring scalability. Rather than relying on centralized training or frequent global state exchanges, federate aggregation allows clusters to train locally while still benefiting from shared knowledge. This approach significantly reduces communication overhead and makes the framework practical for large-scale deployments. The control overhead introduced by model updates remains modest relative to the performance gains achieved.

Despite its advantages, the proposed methodintroducesadditional computational complexity compared to classical routing protocols. However, the use of lightweight GNN architectures and periodic training schedules ensures that the approach remains feasible for resource- constrained sensor nodes. Moreover, training can be performed offline or at the sink, further mitigating on-node computational burden.

Overall, the results suggest that learning-based routing strategies, when carefully designed for energy efficiency and scalability, offer a promising alternative to traditional WSN routing protocols. The proposedframeworkdemonstratesrobustness under diverse network conditions and provides a strong foundation for future intelligent WSN deployments.

Conclusion

This study presented an AI-driven energy-efficient routing framework for large-scale wirelesssensornetworks,integrating graphneural networks with deep reinforcement learning to optimize routing decisions and extend network lifetime. By capturing both topological structure and dynamic energy states, the proposed approach enables intelligent, adaptive path selection that outperforms conventional routing protocols in terms of energy efficiency, packet delivery ratio, and latency. Simulation results confirm that the proposed framework significantly prolongs network lifetime by balancing energy consumption among sensor nodes and avoiding energy hotspots commonly observed in shortest-path and cluster-based routing schemes. The use of federated learning further enhances scalability and privacy by enabling decentralized training without excessive communication overhead. Even in dense

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and high-traffic scenarios, the framework maintains reliable data delivery and low end-to-end delay.

From a practical perspective, the framework is well suited for real-world deployments such as environmental monitoring, smart agriculture, and industrial Internet of Things applications, where long-term sustainability and minimal maintenance are critical. Although the approach introduces additional computational overhead compared to traditional protocols, the use of lightweight learning models and periodic updates ensures feasibility on resource-constrained sensor nodes.

Future research may focus on incorporating mobility-aware routing to support mobile sinks and sensor nodes, as well as extending the framework to heterogeneous sensor networks with varying hardware capabilities. Additionally, integrating energy harvesting models and security- aware routing objectives could further enhance network robustness. Real-world testbed implementations and hardware-in-the-loop experiments would also be valuable for validating the framework under practical deployment conditions.

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