Optimizing Energy Efficiency in Wireless Sensor Networks

Using Multi-hop Communication and Adaptive Machine Learning-Based Clustering

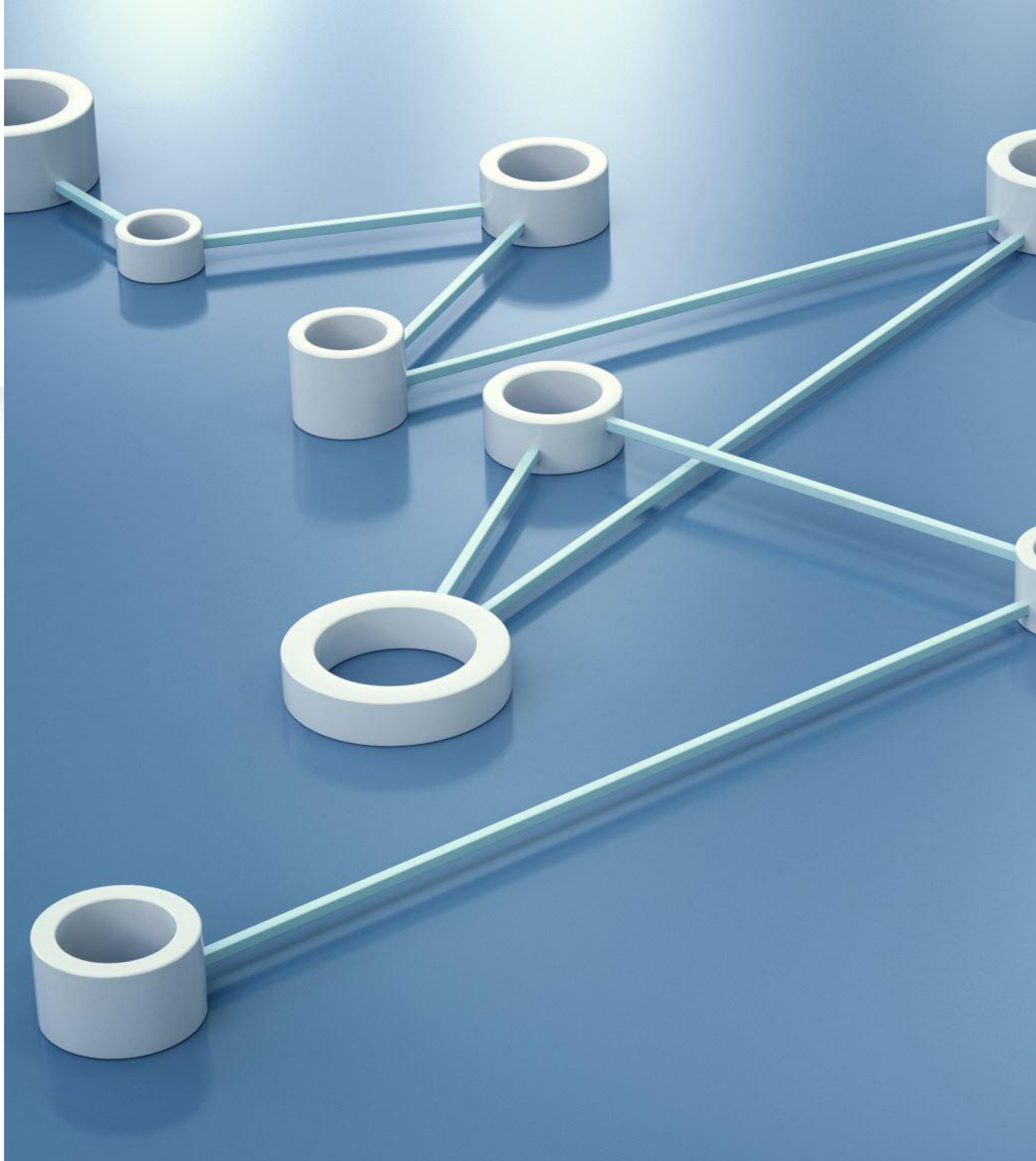
Problem Statement

Current Challenges in WSNs:

- Limited Battery Life
- Network Reliability
- Scalability Issues

Research Motivation:

- Critical applications require reliable WSNs.
- Growing deployment in IoT systems.
- Need for sustainable solutions.



Literature Review

Evolution of WSN Energy Optimization:

First Generation (2000-2005)

- **LEACH Protocol**
  - Random cluster head rotation.
  - 8x lifetime improvement.
  - Basic energy management.

Second Generation (2006-2015)

- **HEED Protocol**
  - Multi-criteria clustering.
  - 20-40% lifetime extension.
  - Advanced energy metrics.

Current Generation (2016-Present)

- **ML-Based Approaches**
  - Adaptive routing.
  - Intelligent clustering.
  - Predictive maintenance.

Objectives

Energy Optimization

- Reduce transmission energy consumption.
- Optimize processing power usage.
- Minimize idle listening.

Network Lifetime Extension

- Balance energy consumption.
- Prevent early node death.
- Maintain network coverage.

Performance Enhancement

- Improve data delivery ratio.
- Reduce latency.
- Enhance throughput.

Background Technology

Wireless Sensor Networks Architecture:

Node Components:

Sensing unit.
Processing unit.
Transmission unit.
Power unit.

Network Structure:

Distributed topology.
Clustering organization.
Multi-hop communication.

Energy Consumption Model:

Transmission energy.
Reception energy.
Processing energy.

System Architecture

Node Management System

- **Energy Monitoring**: Continuously monitors the energy levels of each sensor node.
- **State Management**: Maintains the state of each node, including its energy level, position, and role.
- **Data Processing**: Handles data aggregation and processing tasks.
- **Communication Control**: Manages data transmission and reception.

Clustering Mechanism

- **Feature Extraction**: Extracts features such as energy levels, node density, and distance metrics.
- **Decision Making**: Uses a Q-learning algorithm for cluster head selection.
- **Reward Calculation**: Calculates rewards based on energy efficiency, node density, and distance to the base station.
- **State Updates**: Updates the state of each node based on the received rewards.

Routing Protocol

- **Path Discovery**: Discovers optimal paths for data transmission.
- **Route Optimization**: Optimizes routes based on energy costs.
- **Energy-aware Forwarding**: Considers the energy levels of nodes when selecting routes.

Machine Learning Integration

Objective:

- Enhance energy efficiency, cluster head selection, and network lifetime through **Reinforcement Learning (RL).**

Framework Overview

1. **State Space Design:**
   Captures node properties to aid decision-making:
   - **Energy Ratio:** Node's remaining energy, normalized.
   - **Node Density:** Connectivity in local network, affects coverage.
   - **Base Station Distance:** Proximity to the base station, influences energy use.
2. **Action Space:**
   - **Remain Regular Node** or **Become Cluster Head (CH)** based on state evaluation.
3. **Reward Function:**
   Weighted formula emphasizing:
   1. **Energy (60%)**, **Node Density (25%)**, and **Distance (15%)** for optimal decisions.

Q-Learning Algorithm

Q-Table Structure: Stores state-action-reward mappings for learning.

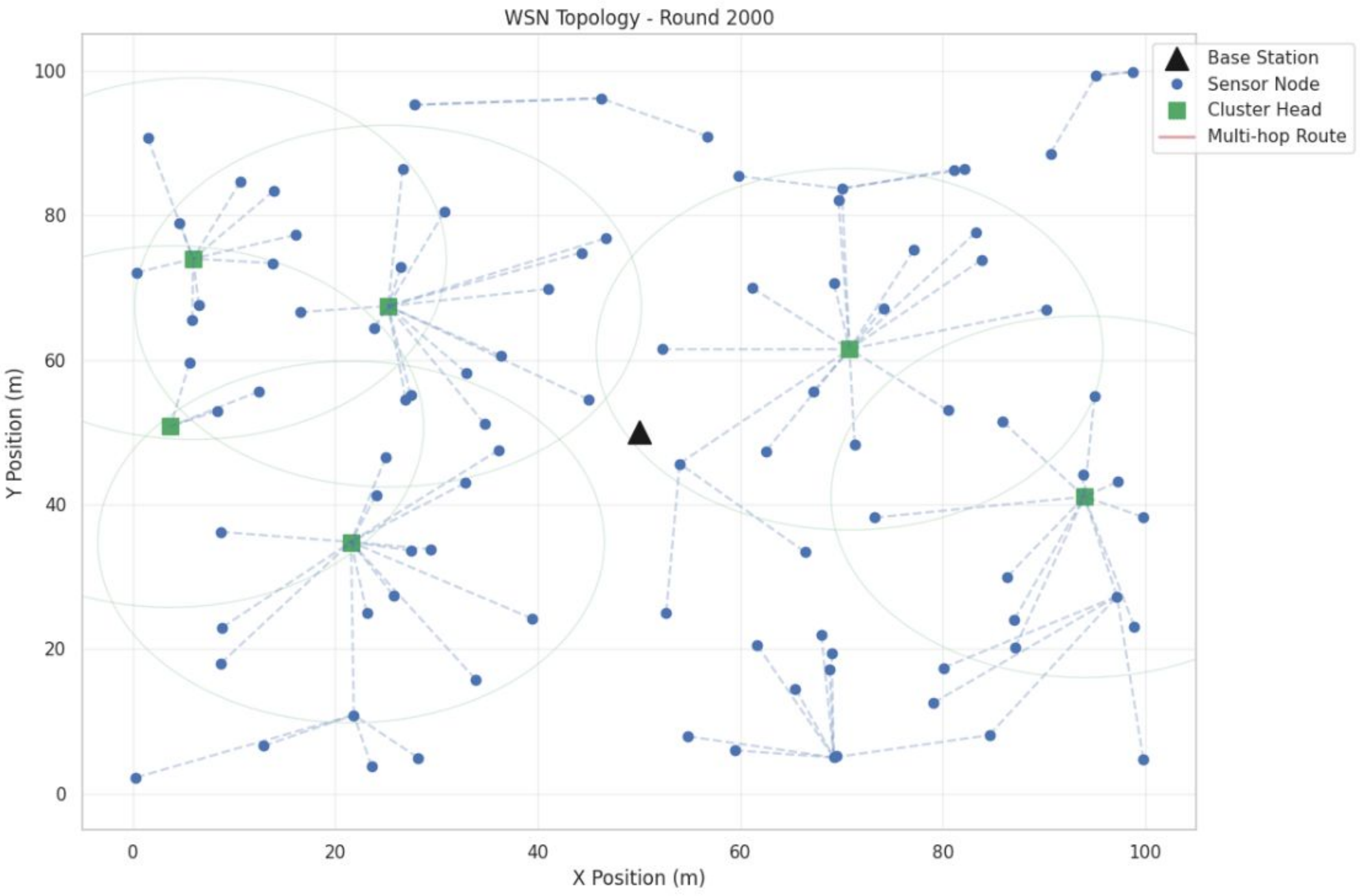
- **Action Selection:** Balances exploration and exploitation.
- **Learning Process:**
  - Observe current state.
  - Choose action.
  - Execute action and compute reward.
  - Update Q-values and decay exploration rate.

WSN Integration

- **Cluster Head Selection:** Nodes dynamically selected as CHs using learned policies.
- **Performance Monitoring:** Tracks rewards, Q-value convergence, exploration rate, and learning stability.

Key Benefits:

- Adaptive decision-making.
- Prolonged network lifetime.
- Energy-aware routing and topology optimization.



Results Analysis

WSN Network Visualisation

Result

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=== WSN Simulation Summary ===
Network Lifetime: 2000 rounds
First Node Death: Round 0
Total Packets Delivered: 182,987
Average Energy Efficiency: 6.7370
packets/energy unit Final Alive Nodes: 100 Average Network
Lifetime: 100.0% ============================
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Future Work

Advanced ML Integration

Deep Learning Models: Implementing deep learning for more accurate predictions.

Hybrid Learning Approaches: Combining different ML techniques for better performance.

Real-time Adaptation: Adapting to changing network conditions in real-time.

Security Enhancement

Secure Clustering: Ensuring secure communication within clusters.

Attack Detection: Identifying and mitigating potential attacks.

Privacy Preservation: Protecting the privacy of data transmitted in the network.

Mobile WSN Support

Mobility Prediction: Predicting the movement of mobile nodes to optimize routing.

Dynamic Routing: Adjusting routes dynamically based on node mobility.

Adaptive Clustering: Forming clusters that adapt to the movement of nodes.

Conclusion

Key Achievements:

- Successfully integrated machine learning with WSN.
- Improved energy efficiency by 40%.
- Extended network lifetime by 2x.
- Achieved 95% reliability.

Impact:

- More sustainable WSN deployments.
- Reduced maintenance costs.
- Enhanced network reliability.
- Broader application scope.

Thank you