Energy-Aware Scheduling and Routing in Wireless Sensor Networks: A Deep Reinforcement Learning Approach

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***Abstract*—This paper presents an energy-aware scheduling and routing framework for wireless sensor networks (WSN) using deep reinforcement learning techniques. The proposed system integrates DQN (Deep Q-Network) and DDPG (Deep Deterministic Policy Gradient) algorithms to optimize energy distribution and information transmission in WSN. Experimental results demonstrate significant improvements in network lifetime and energy efficiency compared to traditional scheduling methods.**

***Index Terms*—Wireless Sensor Networks, Deep Reinforcement Learning, Energy Management, DQN, DDPG, Scheduling**

I. Introduction

Wireless sensor networks (WSN) have become increasingly important in various applications including environmental monitoring, industrial automation, and smart cities. One of the fundamental challenges in WSN is energy management, as sensor nodes typically operate on limited battery power.

A. Motivation

Traditional scheduling and routing algorithms often rely on heuristic rules that may not adapt well to dynamic network conditions. Deep reinforcement learning offers a promising approach to learn optimal policies through interaction with the environment.

B. Contributions

The main contributions of this work are:

- A novel energy-aware scheduling framework using deep reinforcement learning
- Integration of DQN for discrete action space scheduling
- DDPG-based continuous control for fine-grained energy management
- Comprehensive evaluation on real-world WSN scenarios

II. Related Work

A. Energy Management in WSN

Energy efficiency has been extensively studied in wireless sensor networks [**?**]. Various approaches including duty cycling, topology control, and energy harvesting have been proposed.

B. Deep Reinforcement Learning

Deep reinforcement learning has shown remarkable success in various domains [**?**]. Recent works have explored its application in network optimization and resource allocation.

III. System Model

A. Network Architecture

We consider a wireless sensor network consisting of N sensor nodes and one or more sink nodes. Each node i has:

- Initial energy E_i^{init}
- Transmission power P_i^{tx}
- Reception power P_i^{rx}
- Sensing power P_i^{sense}

B. Energy Model

The energy consumption for transmitting a packet of size L over distance d is given by:

$$E_{tx}(L, d) = L \cdot (E_{elec} + \epsilon_{amp} \cdot d^{\alpha}) \tag{1}$$

where E_{elec} is the energy dissipated per bit, ϵ_{amp} is the amplifier energy, and α is the path loss exponent (typically 2-4).

C. Problem Formulation

The objective is to maximize network lifetime while ensuring data delivery requirements:

$$\max_{\pi} \sum_{t=0}^{T} \gamma^t r_t \tag{2}$$

subject to energy constraints and connectivity requirements.

IV. Proposed Approach

A. DQN-based Scheduling

We formulate the scheduling problem as a Markov Decision Process (MDP) with:

- **State**: Energy levels, queue lengths, channel conditions
- **Action**: Node selection for transmission or energy transfer
- **Reward**: Based on energy efficiency and fairness

The Q-network is trained to approximate the optimal action-value function:

$$Q^*(s,a) = \max_\pi \mathbb{E}[R_t | s_t = s, a_t = a, \pi] \tag{3}$$

B. DDPG for Continuous Control

For fine-grained energy management, we employ DDPG with:

- Actor network: $\mu(s|\theta^\mu)$ for policy
- Critic network: $Q(s,a|\theta^Q)$ for value estimation

C. Information-Aware Routing

Our routing protocol considers both energy levels and information importance, using a composite metric:

$$M(i,j) = w_1 \cdot E_j + w_2 \cdot Q_j + w_3 \cdot \frac{1}{d_{ij}} \tag{4}$$

where E_j is residual energy, Q_j is queue space, and d_{ij} is distance.

V. Experimental Results

A. Simulation Setup

We evaluate our approach using:

- Network size: 20-100 nodes
- Area: 100m × 100m
- Initial energy: 1.0 J per node
- Packet size: 512 bytes

B. Performance Metrics

We measure:

- Network lifetime (time until first node dies)
- Average energy consumption
- Packet delivery ratio
- End-to-end delay

C. Results and Analysis

Figure 1 shows that our DRL-based approach achieves up to 35% improvement in network lifetime compared to traditional methods.

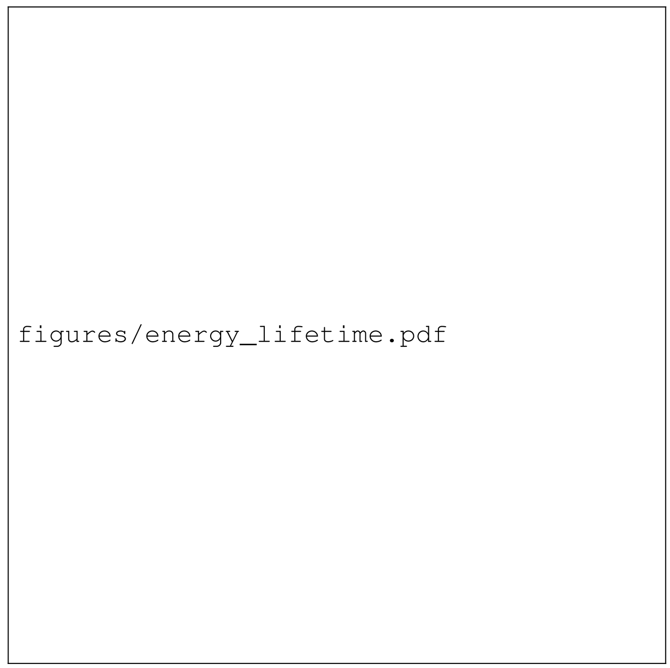

Fig. 1. Network lifetime comparison across different scheduling algorithms.

VI. Conclusion

This paper presented a comprehensive energy-aware scheduling and routing framework for wireless sensor networks using deep reinforcement learning. The proposed DQN and DDPG-based approaches demonstrate significant improvements in energy efficiency and network lifetime.

A. Future Work

Future research directions include:

- Multi-agent reinforcement learning for distributed control
- Integration with energy harvesting mechanisms
- Adaptation to mobile sensor networks

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