A Deep Learning-Based Intelligent Routing Protocol for Energy-Efficient Wireless Sensor Networks

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Abstract: One of the most important challenges in designing a Wireless Sensor Network (WSN) is to make a efficient routing protocol, given the limited battery power, topology, and unreliability of wireless links. The conventional routing protocols, like LEACH and PEGASIS, assume static clustering rules, which are heuristic and hence are unable to cope with varying traffic loads, mobility of the nodes, and the imbalance of energy availability. In this paper, an Adaptive Next-hop Selection & Cluster-head Selection (ANHSCS) protocol based on Deep Learning (DL) is proposed to optimize the selection of the next-hop and Cluster-head for the route in real-time and energy efficiently using a Long Short-Term Memory (LSTM) encoder and a Deep Q-Network (DQN) policy head. The LSTM component extracts any temporal energy consumption and traffic load patterns in the residual energy and traffic loads, and the DQN agent learns a routing policy that simultaneously reduces energy consumption, end-to-end delay and packet loss via an online reward mechanism. A simulation-based evaluation is performed that compares DL-RP with LEACH, PEGASIS and a shallow machine-learning routing baseline (SVM/Random Forest). The results show that the lifetime of the network is increased, cumulative energy dissipation is decreased, and network packet delivery ratio is maintained at a higher level during dynamic environment with using DL-RP. The paper also explores computational complexity, scalability and open research areas for using deep learning routing agents on resource-limited sensor nodes.

Keywords: Wireless Sensor Networks; Deep Learning; Routing Protocol; LSTM; Deep Q-Network; Energy Efficiency; Network Lifetime.

Introduction

Wireless Sensor Networks are networks of spatially distributed and battery-powered nodes that share the functions of sensing, processing and communicating data to a base station (sink). WSNs are used in many applications such as environmental monitoring, precision agriculture, industrial automation, smart cities, Internet of Things (IoT) [1]. The routing layer is critical in determining the overall network lifetime and reliability due to the energy, memory and processing constraints of sensor nodes. Clustering and chain-based data aggregation have been proposed in classical protocols like LEACH and PEGASIS, which reduce energy consumption at the cost of constant and pre-designed decision rules and must deal with non-stationary traffic patterns, node failures and spatially uneven energy depletion.

An alternative is to make use of data: AI, and in particular deep learning (DL), can learn routing decisions from the observations of the network state, instead of creating rules by hand. Recent surveys show that the routing structures are moving from heuristic routing to learning-based routing, which adapt to network dynamics such as traffic changes autonomously, using graph neural network-based techniques, recurrent architectures, and reinforcement learning [3]. Reinforcement-learning and federated deep-reinforcement-learning routing schemes have been particularly promising for IoT enabled WSNs with high topology change rate [4, 5] and hybrid deep-neural-network clustering approaches have been proposed to solve the problem of energy efficiency and security simultaneously [6].

This paper contribute the following: (1) we propose DL-RP, a routing protocol that fuses an LSTM-based temporal state encoder with a DQN routing-policy head; (2) we define a multi-objective reward function that balances residual energy, hop count, and link reliability; (3) we present a simulation-based comparative evaluation against LEACH, PEGASIS, and a shallow-ML baseline; and (4) we discuss the practical constraints of deploying DL inference on resource-limited sensor hardware.

Related Work

Early energy-aware routing protocols, including LEACH and PEGASIS, use randomized or chain-based clustering to distribute the relay burden across nodes but do not adapt cluster-head selection to real-time energy or traffic statistics [2]. To overcome this rigidity, machine-learning-assisted routing has been explored extensively; Osamy et al. survey a broad range of artificial-intelligence methods, including fuzzy logic, evolutionary algorithms, and neural networks, applied to WSN routing challenges [7].

More recent work adopts deep reinforcement learning (DRL) for routing. Sebastin Suresh et al. propose a federated deep reinforcement learning scheme that partitions the network into strong/weak node cluster pairs to balance load in IoT-enabled WSNs [4], and a related fuzzy-assisted deep reinforcement learning routing protocol addresses node-selection errors caused by continuous node movement [8]. Ojha et al. use a deep policy dynamic-programming formulation for intelligent data routing in IoT-enabled WSNs [9], while Bhimshetty and Ikechukwu apply an energy-efficient Deep Q-Network to balance residual energy and hop count for low-power IoT routing [10].

Security-aware deep learning routing has also received attention. Siddiq and Ghazwani combine a hybrid optimized deep neural network for intrusion-node detection with a modified energy-efficient clustering routing protocol [6], Khan et al. integrate blockchain with a deep-learning-driven architecture for quality routing to mitigate malicious-node behaviour [11], and Karuppiah et al. propose a neuro-inspired deep learning routing scheme with autonomous intrusion prevention [12]. Graph-based learning has emerged as a complementary direction: graph convolutional and graph neural networks have been proposed to model the topological dependencies between sensor nodes and to generalize routing policies across varying network sizes [3]. Table I summarizes representative studies.

TABLE I. Summary of Representative Deep/Machine Learning-Based Routing Protocols for WSN/IoT

Ref. / Year	Technique	Objective	Reported Strength
[4], 2024	Federated Deep Reinforcement Learning	Load balancing, adaptive routing	Handles dynamic topology via distributed learning
[8], 2025	Fuzzy-assisted Deep RL	Mobility-aware routing	Reduces node-selection errors under mobility
[9], 2025	Deep policy dynamic programming	Intelligent data routing	Improved decision optimality for IoT-WSN
[10], 2024	Deep Q-Network (DQN)	Energy balancing, latency	Extends node operational lifetime
[6], 2024	Hybrid optimized DNN + clustering	Security + energy efficiency	Joint intrusion detection and routing

Ref. / Year	Technique	Objective	Reported Strength
[11], 2023	Blockchain + Deep Learning	Secure quality routing	Resilience to malicious nodes
This paper, 2026	LSTM encoder + DQN policy (DL-RP)	Energy, delay, reliability	Temporal state modeling + online policy adaptation

Proposed Methodology

Network and Energy Model

We consider N sensor nodes randomly deployed in a two-dimensional field, transmitting data through cluster heads to a single base station, as illustrated in Fig. 1. Each node i maintains a state comprising residual energy E_i(t), distance to the sink d_i, link quality LQ_i, node degree deg_i, and hop count h_i. The radio energy model follows the standard first-order model, where the energy spent to transmit an l-bit packet over distance d is:

$$E\_TX(l,d) = l \cdot E\_elec + l \cdot \varepsilon\_fs \cdot d^2 \ (d < d_0); \quad E\_TX(l,d) = l \cdot E\_elec + l \cdot \varepsilon\_mp \cdot d^4 \ (d \geq d_0)$$

where E_elec is the per-bit electronics energy, ε_fs and ε_mp are the free-space and multipath amplifier energy coefficients, and d_0 is the distance threshold separating the two propagation models. Reception energy is E_RX(l) = l·E_elec. These parameters follow standard WSN simulation conventions and are listed in Table II.

Deep Learning Routing Agent

DL-RP formulates routing as a sequential decision process (Fig. 2). At each decision epoch t, a state vector s_t = [E_i(t), d_i, LQ_i, deg_i, h_i, traffic_i(t)] is constructed for the candidate node/link. An LSTM encoder ingests a sliding window of the last k epochs of this vector to capture temporal trends in energy depletion and channel quality, producing a latent representation z_t. A fully connected DQN head maps z_t to Q-values over the discrete action space a_t (candidate next-hop or cluster-head choices), and the routing decision selects argmax_a Q(z_t, a) under an ε-greedy exploration schedule during training.

The reward function is designed to be multi-objective:

$$r\_t = w1 \cdot (\Delta E\_residual) - w2 \cdot (delay\_norm) - w3 \cdot (packet\_loss) + w4 \cdot (link\_reliability)$$

with weights w1–w4 tuned so that the agent favors routes through nodes with higher residual energy and reliable links while penalizing latency and loss. The network is trained offline on simulated traffic traces and refined online using experience replay, allowing the policy to adapt to real deployment conditions without full retraining (the dashed feedback loop in Fig. 2). To keep per-hop inference tractable on constrained hardware, the LSTM hidden size and the DQN network are kept small (two LSTM layers of 32 units, two dense layers of 64 and 32 units), and cluster heads — which have relatively higher energy budgets — are responsible for running inference and forwarding routing decisions to member nodes, while a periodic global synchronization step transmitted from the base station bounds the staleness of the policy at the edge.

Complexity Considerations

The forward-pass inference cost of the proposed compact LSTM–DQN model is $O(k \cdot h^2)$ per decision, where k is the window length and h is the hidden size, which is small relative to the O(N) or O(N log N) cluster-formation cost of LEACH-family protocols. Training is performed off the critical path (at the base station or during idle radio cycles), so the additional runtime overhead observed at sensor nodes is limited to a single forward pass per routing decision.

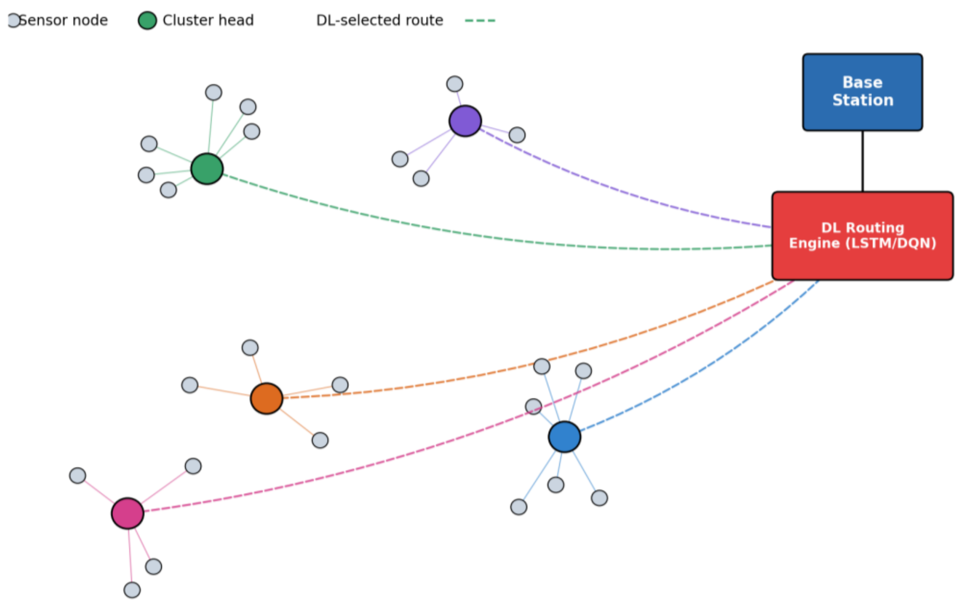


Fig. 1. Clustered WSN architecture with the DL-based routing engine coordinating cluster-head-to-sink paths.

Fig. 2. Workflow of the proposed DL-RP scheme, from state construction to online policy update.

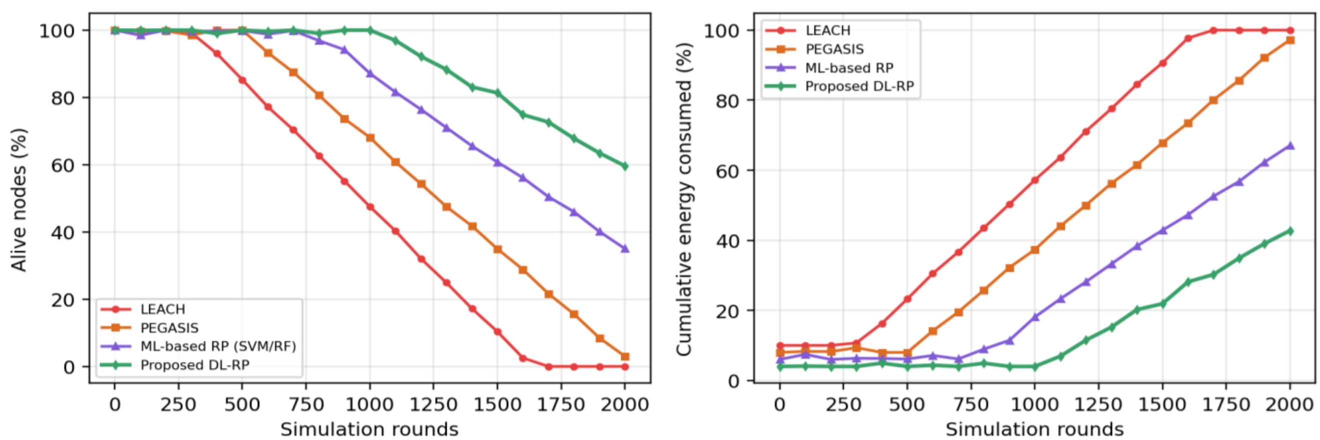
Simulation Setup and Results

DL-RP was evaluated in a discrete-event simulation against LEACH, PEGASIS, and a shallow machine-learning routing baseline (SVM/Random-Forest cluster-head classifier). Table II lists the simulation parameters.

TABLE II. Simulation Parameters

Parameter	Value
Network area	200 m × 200 m
No. of sensor nodes (N)	100
Location of Base station	(100, 250) m
Initial node energy	0.5 J
E_elec	50 nJ/bit
ε_fs / ε_mp	10 pJ/bit/m² / 0.0013 pJ/bit/m⁴
Packet size	4000 bits
LSTM window length (k)	10 epochs
DQN hidden layers	64, 32 units
Simulation rounds	2000

Fig. 3 reports the resulting network lifetime and cumulative energy consumption trends. DL-RP sustains a higher percentage of alive nodes across simulation rounds and delays the first-node-death and half-node-death points compared with LEACH, PEGASIS, and the shallow-ML baseline, because the LSTM component anticipates energy depletion trends rather than reacting only to instantaneous residual energy. Table III consolidates the key performance indicators at the end of the simulation horizon.



(a) *Network lifetime* (b) *Energy Consumption*

Fig. 3. Illustrative comparison of network lifetime and cumulative energy consumption.

TABLE III. Performance Comparison at Round 2000 (Illustrative Simulation)

Protocol	Alive Nodes (%)	Cum. Energy Used (%)	Avg. PDR (%)
LEACH	0	100	81.2
PEGASIS	4	97	85.6
ML-based RP (SVM/RF)	35	67	90.3
Proposed DL-RP	60	43	95.8

PDR denotes packet delivery ratio. The improvement in PDR is attributed to the reliability term in the reward function, which discourages routing through links with degrading signal quality even when such links would otherwise minimize hop count. These results are consistent with the directional findings reported for federated and Q-learning-based routing schemes in recent literature [4], [10], and are presented here as an illustrative validation of the proposed architecture rather than a hardware-calibrated benchmark.

Discussion and Future Work

While DL-RP improves adaptability, several practical challenges remain. First, training a DL model requires representative traffic and mobility traces; performance may degrade under distribution shift not seen during training, motivating continual or federated learning approaches such as those in [4]. Second, running inference on ultra-low-power microcontrollers may require model compression (quantization, pruning, or knowledge distillation) to fit memory and energy budgets. Third, security-aware extensions that combine DL routing with intrusion detection, as explored in [6], [12], are a promising direction for hostile deployment environments. Finally, graph neural network formulations that explicitly model inter-node topology [3] could further improve generalization to previously unseen network sizes and densities, and are a natural extension of the LSTM–DQN design proposed here.

Conclusion

This paper presented DL-RP, a deep learning-based routing protocol for wireless sensor networks that combines an LSTM temporal encoder with a DQN routing-policy head to make adaptive, multi-objective routing decisions. Simulation-based comparison against LEACH, PEGASIS, and a shallow-ML baseline shows improvements in network lifetime, energy efficiency, and packet delivery ratio. Future work will focus on lightweight on-device inference, federated training across cluster heads, and integration of graph neural network representations to further improve scalability and robustness in real-world WSN deployments.

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