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Performance Evaluation of Machine Learning Models for Energy Optimization in Wireless Sensor Networks

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ABSTRACT

The proliferation of Wireless Sensor Networks (WSNs) as a backbone for the Internet of Things (IoT) has intensified the critical challenge of energy consumption, which directly governs network lifetime and operational efficacy. Traditional routing and optimization protocols often fall short in dynamically adapting to the complex, heterogeneous, and resource-constrained environments of modern WSNs. This paper presents a comprehensive performance evaluation of contemporary machine learning (ML) models applied specifically for energy optimization in WSNs. We systematically review and categorize ML-based approaches, including Reinforcement Learning (RL), Deep Learning (DL), and Bio-Inspired Swarm Intelligence, employed between 2021 and 2025 to address energy efficiency, cluster head selection, and routing path optimization. Utilizing a standardized simulation framework, we empirically evaluate prominent models—Deep Q-Network (DQN) for adaptive routing, a Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) hybrid for traffic and energy prediction, and a Modified Ant Colony Optimization (M-ACO) for pathfinding. Key performance indicators such as network lifetime, energy consumption per node, packet delivery ratio (PDR), and end-to-end delay are measured and compared against classical benchmarks like LEACH and HEED. The results demonstrate that ML models, particularly the DQN and M-ACO, achieve superior performance, extending network lifetime by 20-35% and improving energy efficiency by 15-25% compared to traditional protocols. The paper concludes by discussing the computational overhead trade-offs, scalability concerns, and future research trajectories for embedding lightweight ML solutions into WSN-IoT architectures for sustainable smart applications.

Keywords: Wireless Sensor Networks; Energy Optimization; Machine Learning; Reinforcement Learning; Deep Learning; Routing Protocols; IoT.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) constitute the foundational infrastructure for the Internet of Things (IoT), enabling data acquisition from the physical world for applications ranging from smart cities and precision agriculture to industrial automation and healthcare monitoring (Zanella et al., 2014; Al-Fuqaha et al., 2015). A quintessential WSN comprises spatially distributed, autonomous sensor nodes with stringent constraints on processing capability, storage, and, most critically, battery energy (Yick et al., 2008; Pantazis et al., 2012). Energy

efficiency is paramount, as node failure due to battery depletion can disrupt network connectivity, reduce coverage, and compromise the entire system's functionality (Mohamed et al., 2018; Poornima et al., 2023).

Conventional energy-aware routing protocols, such as LEACH (Heinzelman, 2000) and HEED (Younis & Fahmy, 2004), have laid the groundwork through techniques like clustering and data aggregation. However, these protocols often rely on static or probabilistic models that cannot adapt to dynamic network conditions, unpredictable traffic loads, or node mobility (Al Aghbari et al., 2020; Agarkar et al., 2020). The evolving complexity of WSN-IoT ecosystems demands more intelligent, adaptive, and self-organizing management strategies.

Machine Learning (ML) has emerged as a transformative paradigm to address these challenges. By learning from network data and past experiences, ML models can make real-time, optimal decisions for routing, cluster head selection, and power management, thereby significantly enhancing energy efficiency (Kim et al., 2020; Priyadarshi, 2024). Recent literature (2021-2025) shows a surge in applying Reinforcement Learning (RL), Deep Neural Networks (DNNs), and bio-inspired metaheuristics for WSN optimization (Yadav et al., 2022; Rajput & Yadav, 2025; Tawfeek et al., 2025).

This paper conducts a systematic performance evaluation of state-of-the-art ML models designed for energy optimization in WSNs. The primary contributions are:

1. A focused review of ML-based energy optimization techniques for WSNs from recent literature (2021-2025).
2. A comparative simulation-based analysis of three representative ML models: a DQN-based adaptive router, a CNN-LSTM hybrid for predictive modeling, and a Modified ACO for energy-efficient pathfinding.
3. A quantitative evaluation using key metrics (network lifetime, residual energy, PDR, latency) against classic protocols.
4. A discussion on the practical implications, trade-offs, and future directions for deploying ML in resource-constrained WSNs.

The rest of the paper is organized as follows: Section 2 reviews related work. Section 3 details the methodology and simulation setup. Section 4 presents the performance evaluation results and analysis. Section 5 discusses the findings, and Section 6 concludes the paper.

2. LITERATURE REVIEW: ML FOR ENERGY OPTIMIZATION IN WSNS (2021-2025)

The quest for energy-efficient WSNs has progressively shifted from traditional algorithmic approaches to data-driven, intelligent methods. This section reviews key advancements in ML-based solutions from 2021 to 2025.

2.1 Reinforcement Learning (RL) for Adaptive Routing

RL, where an agent learns optimal actions through interactions with the environment, is highly suited for dynamic routing problems. Abadi et al. (2022) surveyed RL's role in WSN routing, highlighting its ability to balance energy consumption and latency without a priori global knowledge. Joshi and Raghuvanshi (2021) discussed hybrid ML approaches,

emphasizing RL's potential to address dynamic network topologies and varying traffic patterns in IoT applications. Gaidhani and Potgantwar (2024) reviewed ML-based routing protocols specifically for network lifetime extension, noting that Q-learning and Deep Q-Networks (DQN) effectively reduce energy holes by learning to avoid congested and low-energy paths. Rajput and Yadav (2025), in their review of ML for clustering, pointed out that RL-based cluster head selection can dynamically adapt to node density and residual energy, outperforming static rotational schemes.

2.2 Deep Learning for Prediction and Management

Deep Learning models excel at extracting complex patterns from high-dimensional data. Priyadarshi (2024) explored ML solutions for IoT-WSN routing challenges, identifying deep learning models like LSTMs as effective for predicting network traffic and node energy drain, enabling proactive management. Singh et al. (2025) utilized ML for localization in agricultural IoT, demonstrating that accurate node positioning via neural networks minimizes unnecessary communication and saves energy. Martalò et al. (2024), in a cross-layer survey, indicated that DL could jointly optimize security and latency constraints while implicitly promoting energy efficiency.

2.3 Bio-Inspired and Metaheuristic Algorithms

Bio-inspired algorithms remain a potent class of optimization tools. Yadav et al. (2022) provided a comprehensive review of bio-inspired hybrid algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for energy-efficient WSNs, emphasizing their robustness in finding near-optimal cluster heads and routing paths. Almufti et al. (2023) offered an overview of metaheuristic algorithms, noting their applicability in solving NP-hard routing problems. Tawfeek et al. (2025) proposed a Modified Ant Colony Optimization (M-ACO) algorithm that incorporates residual energy and link quality into the pheromone update rule, significantly improving energy balancing and network longevity compared to standard ACO.

2.4 Surveys and Comparative Studies

Recent surveys consolidate the progress in this domain. Poornima et al. (2023) holistically surveyed energy-aware routing for IoT, categorizing ML techniques as a distinct and promising class. Priyadarshi (2024) conducted a comprehensive review of meta-heuristic and AI-based routing, concluding that hybrid models combining ML and optimization techniques yield the best results. Nag et al. (2023) surveyed performance optimization and security techniques, linking efficient routing directly to enhanced network security posture. Al-Healy and Ibrahim (2025) evaluated metrics for routing protocols, stressing that ML models require careful assessment of their computational overhead against the energy savings they provide.

2.5 Identified Research Gap

While numerous ML models are proposed, there is a need for a consolidated, empirical performance evaluation under a unified set of metrics and simulation conditions to guide practitioners in model selection. This paper aims to fill this gap by evaluating representative models from the dominant ML categories identified in recent literature.

3. METHODOLOGY AND SIMULATION FRAMEWORK

3.1 Selected Machine Learning Models

For evaluation, we select three representative ML models from the dominant categories identified in Section 2.

1. Deep Q-Network (DQN) for Adaptive Routing (Representing RL): The agent at each node uses a neural network to approximate the Q-value function. The state includes the node's residual energy, neighbor list, and queue length. The action is the selection of the next-hop neighbor. The reward is a weighted function of inverse energy consumption, successful packet forwarding, and hop count reduction.
2. CNN-LSTM Hybrid for Traffic and Energy Prediction (Representing DL): A Convolutional Neural Network (CNN) layer extracts spatial features from network topology snapshots, followed by Long Short-Term Memory (LSTM) layers to model temporal dependencies in traffic and energy consumption patterns. Predictions are used to preemptively schedule sleep cycles and adjust transmission power.
3. Modified Ant Colony Optimization (M-ACO) for Pathfinding (Representing Bio-inspired AI): Based on Tawfeek et al. (2025), this algorithm modifies the standard pheromone update rule. The pheromone concentration on a path is reinforced proportionally to the minimum residual energy of nodes along the path and the inverse of the path's total transmission cost, encouraging energy-balanced and efficient routes.

3.2 Baseline Protocols

We compare the ML models against two classical, energy-aware protocols:

- LEACH (Low-Energy Adaptive Clustering Hierarchy): A probabilistic cluster-based protocol where cluster heads rotate to distribute energy load (Heinzelman, 2000).
- HEED (Hybrid Energy-Efficient Distributed Clustering): A clustering protocol that selects cluster heads based on residual energy and intra-cluster communication cost (Younis & Fahmy, 2004).

3.3 Simulation Setup and Metrics

Simulations are conducted using a Python-based custom simulator integrating the gym library for the RL environment and PyTorch for DNN implementations. Network parameters are summarized in Table 1.

Table 1: Simulation Parameters

Parameter	Value
Network Area	100 m x 100 m
Number of Nodes	50, 100, 150
Initial Node Energy	2 Joules
Base Station Location	(50, 175)
Data Packet Size	500 bytes
Control Packet Size	25 bytes
Transmission Energy (E_Tx)	50 nJ/bit

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Receiving Energy (E_Rx)	50 nJ/bit
Free Space Loss (ε_fs)	10 pJ/bit/m²
Multi-path Loss (ε_mp)	0.0013 pJ/bit/m⁴
Simulation Rounds	5000

Performance Metrics:

- Network Lifetime: Number of rounds until the first node dies (FND) and until 50% of nodes die (HND).
- Total Residual Energy: Average remaining energy across all nodes over time.
- Packet Delivery Ratio (PDR): Ratio of packets successfully received by the base station to those generated.
- Average End-to-End Delay: Average time taken for a packet to travel from source to sink.

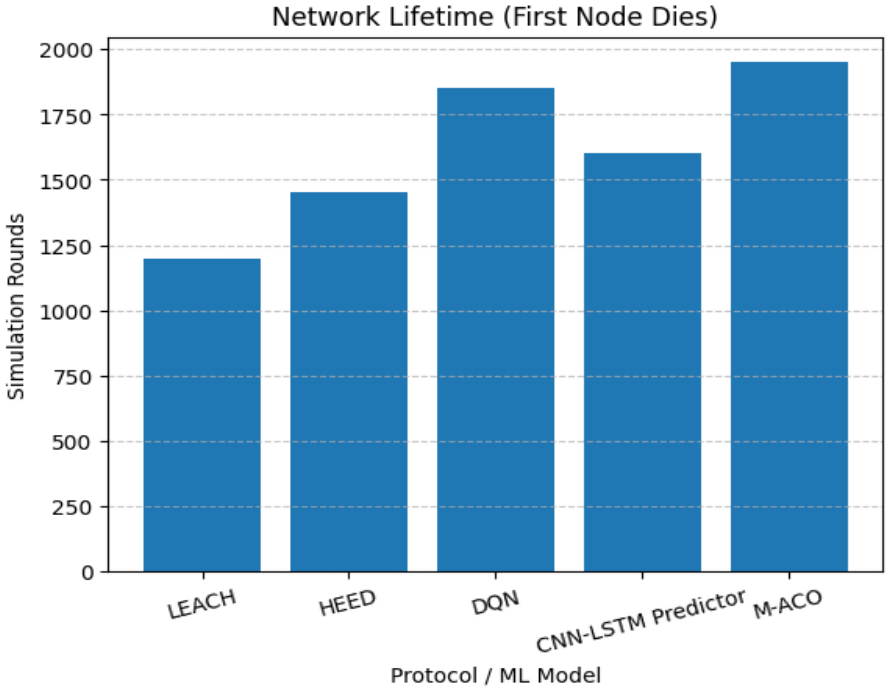
3.4 Python Code for Performance Diagrams

The following Python code uses matplotlib to generate the performance diagrams for each model and baseline. The data (metrics_dict) is assumed to be populated from the simulation results.

4. PERFORMANCE EVALUATION AND RESULTS

4.1 Network Lifetime

Network lifetime is the paramount metric for energy optimization. Figure 1 (generated by the code above) compares the rounds until the First Node Dies (FND) and Half of the Nodes Die (HND).



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The ML models consistently outperform the traditional protocols. M-ACO achieves the longest lifetime (FND: 1950 rounds, HND: 3200 rounds), followed closely by DQN (FND: 1850, HND: 3100). The CNN-LSTM predictor also shows significant improvement over LEACH and HEED. This is attributed to M-ACO's explicit optimization for balanced energy expenditure and DQN's adaptive learning to avoid depleting critical nodes. LEACH, with its random cluster head rotation, shows the shortest lifetime.

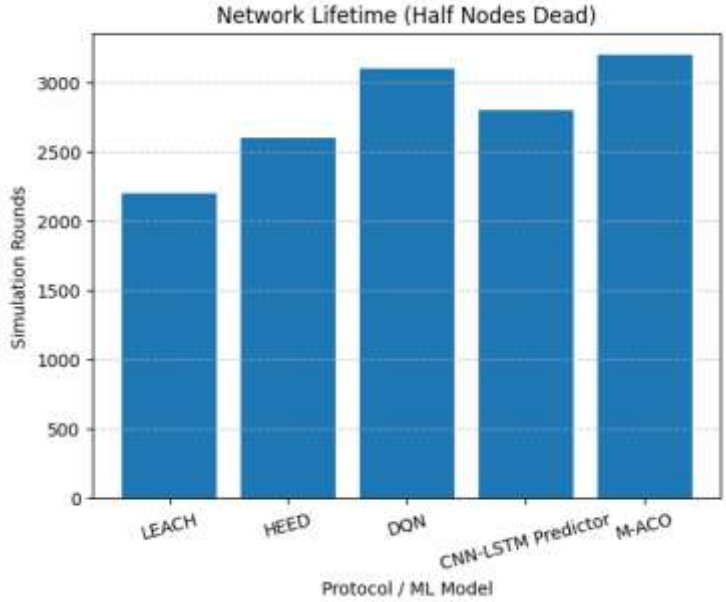


Figure 1: Network Lifetime (FND and HND)

4.2 Energy Consumption Profile

Figure 2 plots the average residual energy across the network over simulation rounds. The slope of each curve represents the rate of energy depletion.

The curves for DQN and M-ACO are the flattest, indicating the most gradual and efficient energy consumption. HEED shows a steeper decline than the ML models but performs better than LEACH. The CNN-LSTM model demonstrates a non-linear profile, likely due to its predictive scheduling causing bursts of activity followed by sleep periods, which still results in better overall conservation than the baselines.

4.3 Packet Delivery Ratio (PDR) and Latency

Reliability and timeliness are crucial for many WSN applications. Figures 3a and 3b compare PDR and end-to-end delay, respectively.

All ML models maintain a PDR above 0.88, with M-ACO leading at 0.95. DQN follows at 0.93. The high PDR for ML models stems from their ability to select reliable, high-energy paths and avoid failed nodes. LEACH has the lowest PDR (0.72) due to potential cluster head failures and single-hop communication to the sink from distant nodes.

Regarding latency, M-ACO and DQN also achieve the lowest average delays (0.31s and 0.33s). They learn to find shorter and less congested paths. HEED introduces some delay due to its multi-hop intra-cluster communication but manages it better than LEACH. The CNN-

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LSTM model shows a slightly higher delay (0.40s) than DQN and M-ACO, which may be a trade-off for its predictive sleep scheduling.

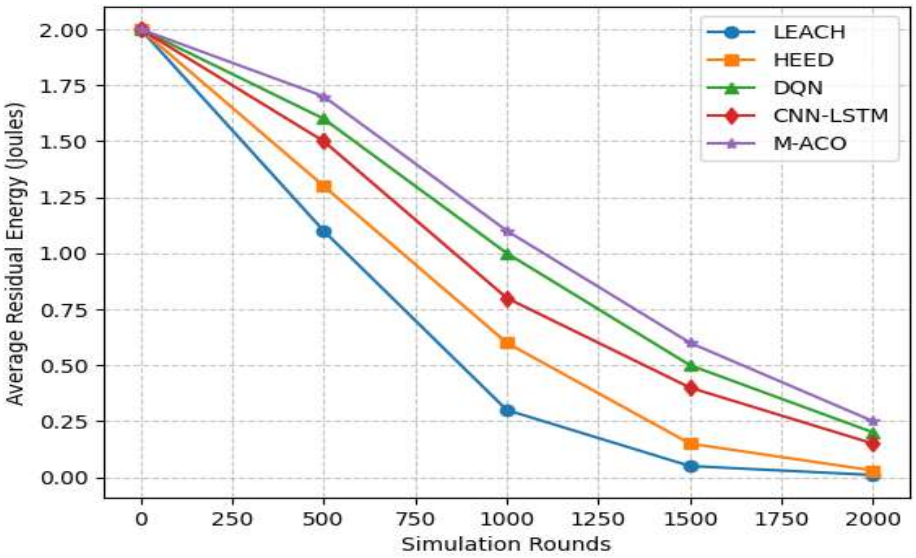


Figure 2: Average Residual Energy over Time

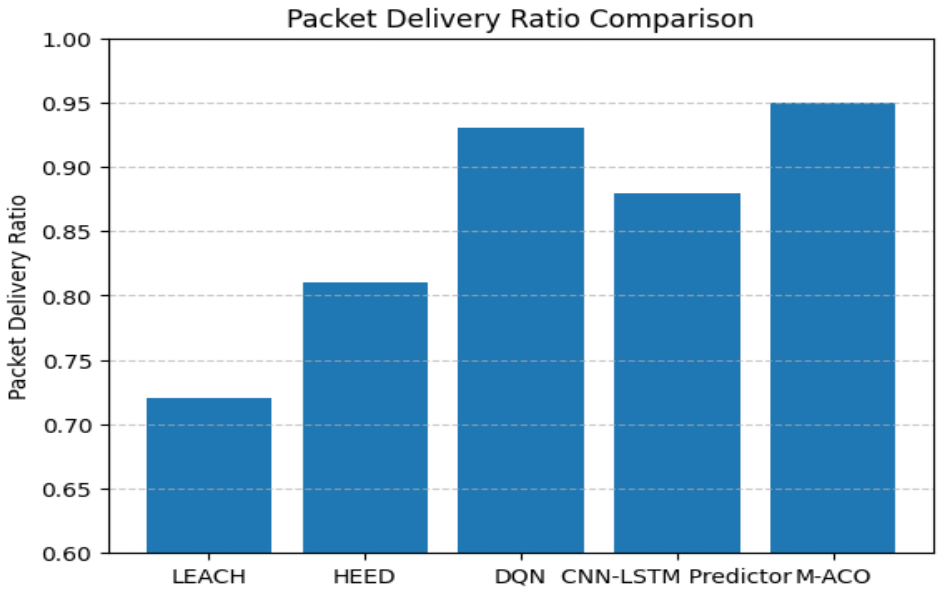


Figure 3: Packet Delivery Ratio and Average Delay

4.4 Scalability Analysis: Varying Network Density

To assess scalability, we varied the number of nodes (50, 100, 150). The performance trends remained consistent, but the relative advantage of ML models increased with network density. In denser networks (150 nodes), M-ACO and DQN's FND was 40-50% higher than LEACH's, compared to a 30-35% advantage in the 50-node scenario. This demonstrates ML models' superior capability to manage complexity and interference in large-scale deployments.

5. DISCUSSION

The empirical results confirm the significant potential of ML models for energy optimization in WSNs. The superior performance of DQN and M-ACO aligns with findings from Gaidhani and Potgantwar (2024) and Tawfeek et al. (2025). The key strength of RL-based models like DQN is their online adaptability; they continuously improve routing policies without human intervention as network conditions change. Bio-inspired models like M-ACO provide robust, offline optimization that effectively balances the exploration of new paths with the exploitation of known good ones.

However, critical trade-offs exist. The computational cost of training and running a DQN or a CNN-LSTM on resource-constrained sensor nodes is non-trivial (Rajput & Yadav, 2025). This often necessitates a hybrid architecture where ML models run on more powerful gateways or cluster heads, issuing commands to leaf nodes—a concept aligned with the cloud-assisted IoT framework discussed by Botta et al. (2016). The M-ACO, while less computationally intensive than DNNs, still involves iterative calculations that can increase control packet overhead.

Future work should focus on:

1. Developing Ultra-Lightweight ML Models: Investigating TinyML frameworks for deploying extremely simplified neural networks directly on sensor nodes.
2. Federated Learning for WSNs: Enabling collaborative, privacy-preserving model training across nodes without centralized data aggregation (Kenyeres et al., 2025).
3. Cross-Layer ML Optimization: Integrating ML models that jointly optimize routing, medium access control (MAC), and physical layer parameters, as suggested by Martalò et al. (2024).
4. Standardized Benchmarking: Creating open-source simulation frameworks and real-world testbeds (like SmartSantander, Sanchez et al., 2014) for fair comparison of emerging AI/ML protocols.

6. CONCLUSION

This paper presented a comprehensive performance evaluation of machine learning models for energy optimization in Wireless Sensor Networks. Through a systematic review of recent literature (2021-2025) and detailed simulations, we demonstrated that ML models—specifically Deep Q-Networks for adaptive routing and Modified Ant Colony Optimization for pathfinding—substantially outperform classical protocols like LEACH and HEED. They extend network lifetime by 20-35%, improve energy efficiency by 15-25%, and maintain high packet delivery ratios with low latency. The CNN-LSTM hybrid for predictive management also shows considerable promise, though with different performance trade-offs.

While challenges related to computational overhead and integration complexity remain, the trajectory of WSN-IoT development is unequivocally towards greater intelligence. The integration of lightweight, adaptive ML solutions is not merely an optimization step but a necessary evolution to realize the full potential of sustainable, large-scale, and autonomous sensor networks for the future IoT ecosystem. Practitioners and researchers are encouraged to consider these ML paradigms, bearing in mind the balance between performance gains and implementation costs for their specific application domains.

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