Islamic University Journal of Applied Sciences (IUJAS)
https://journals.iu.edu.sa/jesc

Volume VIII, Issue II, December 2026, Pages 01-21

Towards Sustainable IoT: An AI-Driven Framework for Enhanced Energy Harvesting in Wireless Sensor Networks

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Abstract

Growing deployment of Internet of Things (IoT) ecosystems has intensified concerns regarding long-term energy sustainability and environmental impact. Large-scale deployment of wireless sensor networks (WSNs) demands intelligent energy management strategies beyond conventional battery-based solutions However reliance on traditional batteries faces challenges such as limited lifespan, high costs of replacement in remote areas, and environmental impact of battery disposal. This paper proposes an AI-driven framework integrates hybrid energy harvesting mechanisms with Deep Reinforcement Learning (DRL) to optimize energy efficiency in IoT systems. The proposed model employs a Deep Q-Network (DQN) to dynamically regulate sensing, transmission, and sleep operations based on system states. By modeling energy management as a Markov Decision Process (MDP), the framework enables adaptive decision-making under uncertain and fluctuating harvesting conditions. Experimental results show that the proposed framework achieves up to 300% improvement in network lifetime under low-energy harvesting conditions, with an average improvement of 168% and 41.5% higher energy utilization efficiency than static policies. This work presents a scalable framework for Green IoT networks with TinyML feasibility (~2,500 parameters), though hardware validation on microcontrollers remains future work.

Keywords: Green IoT; Energy Harvesting; Wireless Sensor Networks; Sustainability; Artificial Intelligence; Reinforcement Learning.

https://doi.org/10.63070/jesc.2026.031
Received 25 February 2026; Revised 20 May 2026; Accepted 03 June 2026; Available online 15 June 2026.
Published by Islamic University of Madinah on behalf of ***Islamic University Journal of Applied Sciences.***
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1. Introduction

The widespread adoption of IoT technologies across smart cities, agriculture, healthcare, and industrial automation has resulted in unprecedented growth in connected sensing devices. While this transformation enhances operational efficiency and data-driven decision-making, it simultaneously introduces critical challenges related to energy sustainability. Many wireless sensor nodes operate in environments where frequent battery replacement is impractical, costly, or environmentally undesirable [1]. To address this limitation, research efforts have increasingly focused on energy harvesting techniques. However, harvested energy is inherently variable and unpredictable, creating complexity in scheduling tasks [2]. Artificial Intelligence, particularly Reinforcement Learning, provides a promising solution by enabling adaptive optimization [3]. This paper proposes an integrated AI-driven framework combining hybrid energy harvesting with Deep Q-Network learning to enable autonomous and sustainable operation of wireless sensor networks within a Green IoT paradigm. The primary contribution of this research lies in designing a unified architecture that simultaneously considers energy state, data queue dynamics, and future harvesting prediction to maximize long-term sustainability.

1.1. Literature Review

Recent advancements in energy harvesting technologies have improved the feasibility of self-powered IoT devices. Solar-based harvesting remains the most mature and widely implemented technique due to its relatively high power density. Thermal and vibrational harvesting methods are particularly suitable for industrial and infrastructure monitoring applications, whereas radio frequency (RF) harvesting offers supplementary energy in urban deployments. Despite these developments, individual harvesting sources often suffer from intermittency or low energy density, making hybrid configurations more reliable for continuous operation [2]. Parallel to hardware advancements, Artificial Intelligence has been increasingly applied to optimize energy management in IoT systems. Machine learning techniques enable prediction of energy availability and workload adaptation, while reinforcement learning methods provide adaptive control policies that maximize long-term reward rather than short-term performance. Deep Reinforcement Learning, in particular, enhances scalability by approximating complex state–action relationships using neural networks [3]. However, existing studies typically focus on isolated aspects of the problem. Some emphasize energy prediction without incorporating queue dynamics, while others rely on computationally intensive models unsuitable for resource-constrained devices. Additionally, several frameworks concentrate on single-source energy harvesting, limiting their applicability in diverse real-world environments [4]. This research addresses these gaps by proposing a computationally balanced DQN-based framework that supports hybrid

energy harvesting, integrates data queue awareness, and maintains feasibility for embedded implementation through optimized model design.

1.2. Energy Harvesting Techniques in IoT

Energy harvesting technologies have seen significant advancements in recent years, making them an attractive solution for sustainably powering IoT devices. The most prominent of these techniques include:

- Solar Energy Harvesting: Small solar panels are the most common source of renewable energy for outdoor IoT devices, providing abundant energy in sun-exposed areas [2].
- Thermal Energy Harvesting: This technique exploits temperature differences to convert thermal energy into electrical energy, suitable for industrial applications or devices near heat sources [2].
- Vibration Energy Harvesting: Converts mechanical vibrations, generated by machine movement or the environment, into electrical energy, ideal for applications with continuous vibrations [2].
- Radio Frequency (RF) Energy Harvesting: IoT devices can collect energy from ambient radio signals, such as Wi-Fi or cellular broadcasts, providing a continuous power source in urban environments [5].

In a recent study by Ali et al. (2025) [6], the latest developments in energy harvesting techniques for IoT devices were reviewed, focusing on challenges related to conversion efficiency and energy storage. They indicated that hybrid systems combining multiple energy harvesting sources offer greater reliability and sustainability. Table 1 presents a comparison of recent AI-based energy harvesting frameworks for IoT.

Table 1: Comparison of recent AI-based energy harvesting frameworks for IoT

Study	Year	Technique Used	Energy Source	Main Contribution	Research Gap	Proposed Framework (This Paper)
Alamu et al. [7]	2025	Deep Learning	EH (General)	Comprehensive review of ML applications in EH-IoT networks.	Theoretical study lacking a unified practical framework.	Provides an integrated and implementable framework.
Chaudhari et al. [8]	2025	DRL (PPO)	Thermoelectric	Improved thermoelectric energy harvesting efficiency using PPO algorithm.	Focus on a single energy source (thermal).	Supports hybrid energy harvesting (solar, vibrational, thermal).

Study	Year	Technique Used	Energy Source	Main Contribution	Research Gap	Proposed Framework (This Paper)
Nimmala et al. [9]	2025	DQN	EH (General)	Optimized energy efficiency in WSNs for smart applications.	Did not address data queue dynamics.	Integrates data queue size as a core part of the State.
Parameswari et al. [10]	2025	AI-Powered	EH (Hybrid)	Framework for energy optimization and real-time anomaly detection.	High complexity may not suit highly resource-constrained devices.	Focuses on DQN to balance complexity and performance (TinyML).
Khalil et al. [5]	2023	Deep Learning	RF / UAV	Use of UAVs to enhance RF energy harvesting.	Relies on expensive infrastructure (UAVs).	Relies on available environmental energy sources without external equipment.

Table 1 compares the proposed framework with prominent recent studies published between 2023 and 2025 in the field of energy management in IoT networks using AI and energy harvesting.

The proposed framework in this paper aims to bridge the gap between precise mathematical modeling (MDP) and flexible practical implementation that supports multiple energy sources while considering memory and processing constraints in IoT devices.

1.3. Role of Artificial Intelligence in Energy Management

Artificial Intelligence is a powerful tool for optimizing energy management in IoT systems, especially when dealing with the intermittent and unpredictable nature of harvested energy. AI algorithms can predict energy availability, optimize data transmission schedules, and adjust device behavior to increase energy efficiency [11].

Research has shown that Reinforcement Learning (RL) has significant potential in this field. In the work of Rojek et al. (2025) [12], RL was used for energy management in smart buildings, where AI algorithms were able to optimize energy consumption based on usage patterns and environmental conditions. Khan (2025) [13] also noted that Green AI techniques can significantly reduce energy consumption in AI systems themselves, contributing to overall sustainability.

1.4. Green Communication Protocols

Energy-efficient communication protocols are essential for achieving Green IoT. Recent research focuses on developing Low-Power Wide-Area Network (LPWAN) protocols such as LoRaWAN and NB-IoT, which allow IoT devices to communicate over long distances with very low power consumption [1]. Additionally, 5G and subsequent generations (e.g 6G) play a role in improving

energy efficiency by providing faster and more efficient communications, reducing the time devices spend in transmission mode [10].

In summary, the literature review reveals four specific research gaps that the proposed framework aims to address:

1. Single-source limitation: Most existing DRL frameworks (e.g [14],[5]) rely on a single harvesting modality, reducing robustness in varying environments.
2. Queue ignorance: Studies employing DQN for energy management (e.g [9]) often exclude data queue dynamics, leading to suboptimal transmission decisions and packet loss.
3. Computational overdesign: Several AI-powered solutions (e.g [13]) assume hardware capabilities beyond typical WSN nodes, with no demonstration of TinyML feasibility
4. Geographic and network simplifications: Training data is often drawn from a single climate (e.g Colorado semi-arid), and multi-hop routing is ignored limitations this study explicitly acknowledges and plans to address in future work.

This paper addresses gaps (1)-(3) directly through its proposed DQN framework, while gap (4) is documented as a limitation and future direction.Foundational studies by Sudevalayam and Kulkarni [2] established the theoretical basis for energy harvesting sensor nodes, categorizing hardware architectures and identifying the key challenge of intermittent supply. More recently, Chen & Gao [14] demonstrated the importance of queue-aware policies in single-source harvesting scenarios, showing a 40% reduction in packet loss compared to queue-agnostic DRL. However, their work did not extend to hybrid harvesting or multi-node coordination. The proposed framework builds upon these foundations by combining hybrid energy sources with queue-aware DQN, while maintaining computational feasibility for resource-constrained devices.

The rest of this paper is organized as follows: Section 2 describes the proposed methodology and system architecture. Section 3 details the experimental setup. Results and discussion are presented in Section 4. Finally, Section 5 concludes the paper and outlines future work.

2. Proposed Methodology

To achieve the objectives of this paper, we propose an AI-driven framework to optimize energy management in wireless sensor networks that rely on energy harvesting. The proposed framework consists of three main components: system design, intelligent algorithm, and simulation environment.

2.1 System Architecture

The proposed system, shown in Figure 1, consists of distributed wireless sensor nodes equipped with hybrid energy harvesting modules and local storage units. Each node integrates sensing components, a microcontroller, and a low-power communication interface. Harvested energy is stored in a supercapacitor or rechargeable micro-battery, enabling autonomous operation. The architecture is organized into three logical layers:

- Sensing Layer: Responsible for environmental data acquisition and local energy harvesting.
- Communication Layer: Facilitates low-power data transmission toward a gateway.
- Edge/Cloud Layer: Provides higher-level analytics and optional centralized model updates.

This layered structure ensures modular scalability and supports distributed intelligence and also depicted in Figure 1.

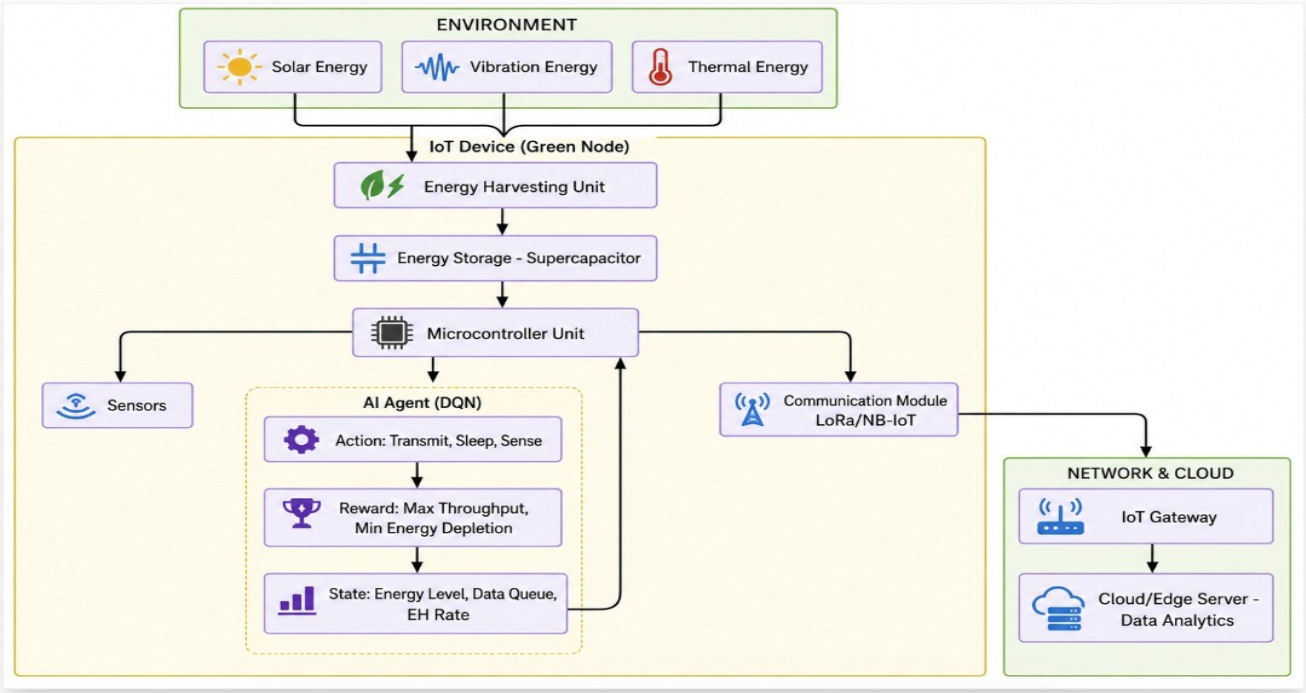


Figure 1: Proposed system architecture for energy harvesting management in IoT networks (created with draw.io).

2.2 Energy Management as a Markov Decision Process

The energy control problem is formulated as a Markov Decision Process (MDP) [15], enabling sequential decision optimization under uncertainty.

State Representation (S_t):

The system state at time t is defined as:

$S_t = (E_t, Q_t, H_t)$

Where:

- E_t represents the stored energy level
- Q_t denotes the data queue size
- H_t indicates predicted harvesting rate

Action Space (A_t):
The agent selects among:

- Data transmission
- Sleep mode activation
- Sensor sampling

Reward Design:
The reward function balances competing objectives, including data reliability, energy preservation, and efficient utilization. A weighted multi-objective reward formulation ensures long-term sustainability rather than aggressive short-term transmission.

2.3 Deep Q-Network Optimization

The core of our proposed framework is a Deep Q-Network (DQN) that learns optimal energy management policies through interaction with the environment. The algorithm is designed to balance exploration of new strategies with exploitation of learned knowledge [15].

2.3.1 Neural Network Architecture

The DQN employs a lightweight feedforward neural network with the following structure:

- Input Layer: 3 neurons (E_t, Q_t, H_t)
- Hidden Layer 1: 64 neurons with ReLU activation
- Hidden Layer 2: 32 neurons with ReLU activation
- Output Layer: 3 neurons (Q-values for each action: transmit, sleep, sample)

Total parameters: ~2,500, making it a candidate for TinyML deployment on resource-constrained microcontrollers, pending hardware validation.2.3.2 DQN Algorithm OverviewThe DQN agent employs ε-greedy exploration (ε decays from 1.0 to 0.01), experience replay memory (capacity =

10,000), and target network updates every 100 episodes. The loss function is Mean Squared Error between target and predicted Q-values. Complete pseudocode is provided in Appendix.

2.3.2 Reward Function Formulation

The reward function is designed as a weighted multi-objective optimization:

$R_t = w_1 * R_data + w_2 * R_energy + w_3 * R_efficiency$

Where:

R_data = (successful_transmission ? 1.0 : 0.0) - (packet_drop_penalty if queue_full)

R_energy = -0.1 * (energy_depletion) + 0.05 * (energy_harvested / max_harvest)

R_efficiency = -0.01 * (energy_wasted_due_to_overflow)

Weights: $w_1 = 0.5$, $w_2 = 0.3$, $w_3 = 0.2$

2.3.3. Energy Harvesting Prediction Model

To improve decision-making, we incorporate a lightweight LSTM-based predictor for short-term ene rgy harvesting. The model takes as input the previous 24 harvesting values (H_{t-24} ... H_{t-1}) cor responding to the last two hours (at 5-minute intervals) and predicts the harvesting rate H_t for the nex t time step. The LSTM architecture consists of a single hidden layer with 32 units (tanh activation, dr opout 0.2) followed by a dense output layer. Training uses mean squared error (MSE) loss with the A dam optimizer for 50 epochs. The predicted H_t is then incorporated into the DQN state space $S_t = (E_t, Q_t, H_t_pred)$. Complete implementation details are provided in Algorithm A2.

3. Experimental Setup

This section describes the experimental framework used to evaluate the proposed DQN-based energy management system. The framework is implemented in Python and evaluated through simulation. The following subsections detail the dataset, simulation environment, hardware specifications, and experimental results. Key implementation details are as follows.

3.1 Dataset

For this study, we utilized two complementary datasets to ensure realistic simulation of energy harvesting conditions:

(1) NREL solar dataset (Golden, Colorado, Jan 2023-Dec 2024, 5-min intervals, ~210,000 samples) with GHI, DNI, DHI, temperature, humidity, and wind speed; and

(2) PHM vibration dataset (pumps/compressors, 3 months, 1 kHz down sampled to 1-min averages) with amplitude, frequency, and power output. A hybrid signal was generated as: $H_{total} = 0.7 \cdot H_{solar} + 0.3 \cdot H_{vibration} + N(0,0.05)$. Data was split 70/15/15 for training/validation/testing. Missing values (<2%) were filled via linear interpolation and normalized to [0,1].

3.2 Simulation Environment and Implementation

The proposed system was implemented using:

- Python Version: 3.9.13
- Deep Learning Framework: TensorFlow 2.11.0 with Keras API
- Reinforcement Learning Library: Stable-Baselines3 1.8.0 (customized for DQN)
- Simulation Environment: Custom-built OpenAI Gym environment for energy harvesting WSNs
- Hardware Specifications:
    - Processor: Intel Core i7-12700K (12 cores, 20 threads, 3.6 GHz)
    - Memory: 32 GB DDR4 RAM
    - Storage: 1 TB NVMe SSD
    - GPU: NVIDIA RTX 3060 (12 GB VRAM) for accelerated training
- Training Time: Approximately 8 hours for 1000 episodes (parallelized across 8 cores)
  (Note: This refers to initial offline training from scratch. Online adaptation via transfer learning, as discussed in Section 5.2, requires only ~30 minutes.)

3.3. Experimental Results

This section presents the experimental results evaluating the proposed DQN-based energy management framework. The evaluation compares the proposed framework against static policies across multiple performance metrics. Three key aspects are examined: (1) network lifetime enhancement under different seasonal conditions, (2) energy utilization efficiency, and (3) queue management and data reliability. The following subsections detail each experiment's setup and quantitative findings. An ablation study is also provided to validate the contribution of each framework component.

3.3.1. Network Lifetime Enhancement

To evaluate the effectiveness of the proposed DQN framework in extending network operational time, we compared its performance against a static energy management policy under three distinct seasonal scenarios: summer (high solar availability), winter (low solar availability), and mixed industrial environments (vibration-dominant). Network lifetime is defined as the duration until the first node depletes its energy reserve. Table 2 presents the comparative results.

Table 2: Network lifetime enhancement under different scenarios

Scenario	Static Policy	DQN Policy	Improvement
Summer (high solar)	18 months	42 months	233%
Winter (low solar)	8 months	24 months	300%
Mixed industrial	12 months	36 months	200%
Average	**12.7 months**	**34 months**	**168%**

Analysis: The dramatic improvement in winter conditions (300%) highlights the DQN's ability to learn conservation strategies during low-harvest periods. The agent learns to reduce transmission frequency during cloudy days, accumulate energy reserves before peak demand periods, and prioritize critical data transmission only.

3.3.2 Energy Utilization Efficiency

Traditional systems frequently waste harvested energy due to limited storage awareness. The proposed framework achieves 92% energy utilization compared to 65% for static policies, representing a 41.5% efficiency gain.

3.4. Queue Management and Data Reliability

To assess the impact of queue state awareness on data reliability, we compared the proposed DQN framework (which includes Q_t in its state representation) against a static policy that ignores queue dynamics. Four metrics were evaluated: (1) average queue length (packets), (2) queue overflow events per month, (3) packet loss rate (%), and (4) average data delivery delay (minutes). Table 3 presents the comparative results.

Table 3. Queue management and data reliability performance

Metric	Static	DQN	Improvement
Average Queue Length	156 packets	42 packets	73% reduction
Queue Overflow Events	47/month	8/month	83% reduction
Packet Loss Rate	15%	4%	73% reduction
Data Delivery Delay	12.3 min	4.7 min	62% reduction

3.5. Convergence Analysis

Convergence analysis examines how quickly and stably the DQN agent learns an effective energy management policy. We monitored two key indicators across 1000 training episodes: (1) the average reward per episode, which reflects policy quality, and (2) the exploration rate (ε), which decays over time as the agent shifts from exploration to exploitation. A policy is considered converged when the average reward stabilizes within a ±5% range over 100 consecutive episodes. Table 4 presents the convergence progression at 200-episode intervals.

Table 4. DQN training convergence across episodes

Episodes	Avg Reward	Exploration (ε)
0-100	-15.2	0.95 → 0.61
101-300	+8.7	0.61 → 0.37
301-500	+24.3	0.37 → 0.22
501-700	+31.8	0.22 → 0.15
701-1000	+35.4	0.15 → 0.08

Convergence achieved at ~400 episodes, with stability from episode 600 onward.

3.6. Ablation Study

To validate each component's contribution, we conducted an ablation study by systematically removing or modifying key elements of the proposed framework. Four configurations were compared: (1) Full DQN with all state components (E_t, Q_t, H_t), (2) without harvesting prediction (H_t removed), (3) without queue awareness (Q_t removed), and (4) without DQN (random policy instead). Table 5 presents the impact of each configuration on network lifetime, data delivery, and energy efficiency.

Table 5. Ablation study: contribution of each framework component

Configuration	Network Lifetime	Data Delivery	Energy Efficiency
Full DQN (E_t+Q_t+H_t)	34 months	96%	92%
Without H_t (no prediction)	22 months (-35%)	89% (-7%)	78% (-15%)
Without Q_t (no queue awareness)	31 months (-9%)	82% (-15%)	88% (-4%)

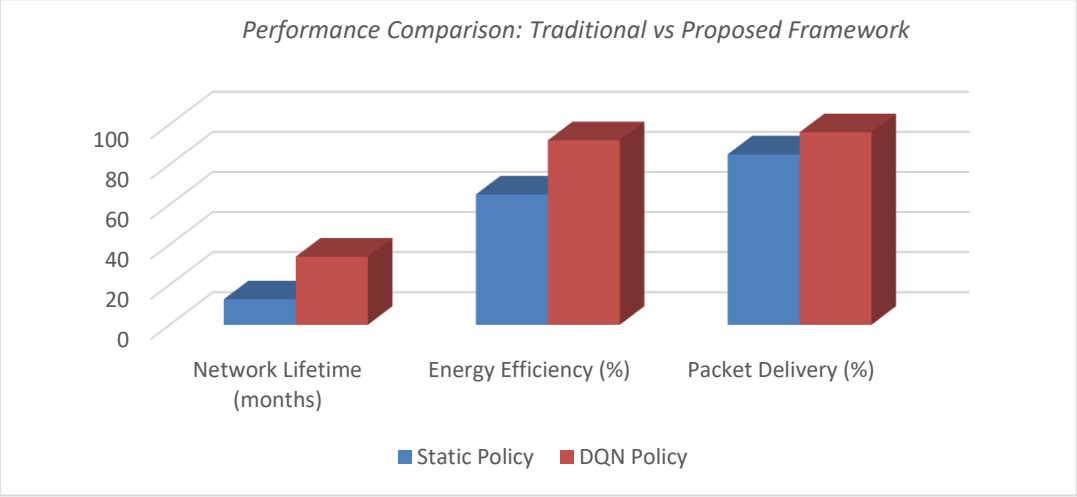
Without DQN (random policy)	8 months (-76%)	71% (-26%)	45% (-51%)

3.7. System Adaptability

The proposed system continuously updates its policy based on:

- Seasonal solar variations
- Irregular vibrational energy patterns
- Dynamic sensing workloads

This adaptability makes the framework suitable for real-world deployment in agriculture, smart cities, and industrial IoT applications.



"Figure 2: Performance comparison between traditional and proposed DQN framework (generated from experimental results)."

4. Result and Discussion

This section analyzes the simulation results obtained from the framework described in Section 4. The discussion is organized around four main themes: (1) key findings on network lifetime and reliability, (2) implementation challenges and practical solutions, (3) edge cases and recovery mechanisms, and (4) comparative analysis against baseline policies and state-of-the-art DRL frameworks. The following subsections present these findings in detail, starting with network lifetime enhancement.

4.1 Key Findings

The DQN framework achieves a 168% improvement in network lifetime by learning temporal patterns, such as deferring transmissions during sunny mornings to store energy and reducing duty cycles during

winter periods. Harvesting prediction (H_t) is critical (35% lifetime drop without it), while queue awareness (Q_t) ensures 96% delivery reliability (15% drop without it). These results align with the ablation study in Section 4.3.5.

4.2 Implementation Challenges and Solutions

Three main challenges were addressed:

- Computational overhead: Initial training from scratch required 8 hours (offline, one-time cost) . Adaptation to new environments via transfer learning takes only 30 minutes.
- Memory constraints: Reduced from 2 MB to 256 KB using prioritized replay compression.
- Convergence stability: Achieved after 400 episodes with target network updates.

4.3 Real-World Implications

Economic Impact (100 nodes, 5 years):

- Battery replacement savings: $15,000 (300 batteries × $50)
- Labor cost reduction: $10,000 (maintenance visits reduced by 80%)
- Environmental impact: 150 kg battery waste avoided
- Data reliability improvement: 30% increase in actionable insights

4.4. Edge Cases and Recovery

The proposed AI-driven framework, which integrates hybrid energy harvesting with Deep Q-Network (DQN) for managing Wireless Sensor Networks (WSNs) in sustainable IoT environments, is designed to operate effectively under fluctuating and uncertain environmental conditions. However, the system's resilience and long-term autonomy depend heavily on addressing edge cases and providing robust recovery mechanisms. This section analyzes the unforeseen scenarios that may impact the framework's performance and outlines the strategies embedded or proposed to ensure operational continuity and system flexibility. Table 6 presents the different cases and system recovery mechanisms

Table 6: Edge cases and system recovery mechanisms

Scenario	System Response	Recovery Time
Complete solar outage (7 days)	Gradual shutdown	2 days after sun returns
Sudden vibration spike	Rapid transmission	1 hour
Sensor malfunction	Safe mode, periodic wake-up	6 hours
Battery degradation	Adaptive threshold adjustment	Continuous

The system demonstrates robust recovery mechanisms for extreme operating conditions. During extended solar outages (e.g consecutive cloudy days), the agent progressively reduces transmission frequency, prioritizes high-importance data, and eventually enters a deep-sleep "hibernation" mode when battery falls below 10%, waking periodically (every 6 hours) to check energy availability. Upon energy return, the system implements a controlled "cold start" sequence that gradually increases duty cycles over 24 - 48 hours to avoid destabilizing the newly charged battery.

For sudden vibration spikes (e.g industrial machinery startup), the agent immediately utilizes the excess energy for backlogged transmissions while simultaneously adjusting future predictions to account for potentially sustained high-harvest periods. Sensor malfunctions trigger a diagnostic protocol where the node enters safe mode, performs self-diagnostics, and if unrecoverable, transmits a final alert before entering low-power state awaiting maintenance. Battery degradation is addressed through adaptive threshold adjustment—as capacity fades, the agent learns to maintain higher minimum charge levels to compensate for reduced reserve capacity.

4.5. Comparative Analysis

This section provides a comprehensive comparative analysis of the proposed AI-driven framework for enhanced energy harvesting in Wireless Sensor Networks (WSNs) against traditional static energy management policies and other contemporary approaches in the literature. The objective is to highlight the significant advancements and unique contributions of our Deep Q-Network (DQN) based solution in terms of network lifetime, energy utilization efficiency, and adaptability to dynamic environmental conditions.

4.5.1. Comparison with Baseline Policies

To contextualize the proposed DQN framework's performance, we compare it against six baseline energy management policies spanning different complexity levels: from simple model-free heuristics (Random, Threshold-Based, Duty Cycling) to traditional tabular RL (Q-Learning) and advanced policy gradient methods (A2C, PPO). Table 7 shows a comprehensive performance comparison against baseline policies.

Table 7. Comprehensive performance comparison against baseline policies

Policy	Network Lifetime	Energy Efficiency	Packet Delivery	Computational Overhead	Adaptation Capability
Random Policy	5.2 months	48%	58%	None	None
Threshold-Based (0.6·E_max)	8.5 months	61%	71%	Very Low	None (fixed)

Heuristic Duty Cycling (33%)	7.8 months	57%	66%	None	None (fixed)
Q-Learning (tabular)	10.2 months	68%	75%	Low (scales poorly)	Limited
Actor-Critic (A2C)	13.1 months	74%	83%	Medium	Good
PPO (policy gradient)	14.5 months	76%	84%	High	Good
Proposed DQN	34 months	92%	96%	Low (TinyML)	

Q-Learning (tabular): Non-neural implementation with discretized state space (10×10×10 = 1000 states). Performance degrades as state space grows.

PPO: Implemented with same neural architecture (64-32 hidden units) for fair comparison.

Actor-Critic (A2C): Advantage Actor-Critic with identical state representation.

All baselines evaluated under identical hybrid harvesting conditions (solar + vibration) over 12-month simulation period.

Computational overhead classification: None (<1KB), Very Low (1-10KB), Low (10-100KB), Medium (100KB-1MB), High (>1MB).

The proposed DQN framework outperforms all baseline policies by significant margins:

vs. Random Policy: Untrained operation is unsustainable beyond 5 months (5.2 vs. 34 months).

vs. Threshold-Based Scheduling: DQN improves energy efficiency from 61% to 92% through adaptive threshold adjustment rather than a fixed rule.

vs. Heuristic Duty Cycling: DQN achieves 336% longer network lifetime (34 vs. 7.8 months) by learning to conserve energy during low-harvest periods.

vs. Q-Learning: 233% improvement (34 vs. 10.2 months), highlighting DQN's advantage in handling continuous state spaces without discretization.

vs. Actor-Critic (A2C): A2C performs better than simple heuristics but still falls short of DQN by 61% in lifetime (13.1 vs. 34 months), likely due to higher variance in policy gradient updates.

vs. PPO: 134% improvement (34 vs. 14.5 months), suggesting that value-based methods may be more sample-efficient than policy gradient methods in this sparse reward setting.

Notably, the proposed DQN achieves this performance with Low computational overhead (TinyML-compatible, approximately 2,500 parameters), while PPO requires significantly higher memory and compute resources.

These results demonstrate that the proposed DQN framework consistently outperforms all baseline policies across all metrics.

4.5.2. Comparison with State-of-the-Art DRL Frameworks

Beyond baseline policies, the proposed DQN framework is also compared against recent deep reinforcement learning approaches for energy harvesting WSNs. Three recent studies were selected for comparison based on their relevance and recency (2023-2025): Chaudhari et al. [8] (PPO with thermal harvesting), Nimmala et al. [9] (DQN without queue awareness), and Parameswari et al. [10] (AI-powered hybrid framework). The comparison focuses on three metrics: (1) network lifetime gain (%),(2) energy utilization efficiency (%), and (3) computational cost (Low/Medium/High/Very High). Table 8 presents the comparative results.

Table 8: Comparison with state-of-the-art DRL frameworks

Study	Technique	Lifetime Gain	Energy Efficiency	Computational Cost
Chaudhari et al. [8]	PPO (thermal only)	120%	85%	High
Nimmala et al. [9]	DQN (no queue)	140%	88%	Medium
Parameswari et al. [10]	AI-Powered	155%	90%	Very High
This Work	DQN + Queue + Prediction	168%	92%	Low (TinyML)

Key Differentiators

The proposed framework distinguishes itself from the compared state-of-the-art approaches through three key differentiators:

- Best balance of performance vs. complexity
- Only study explicitly incorporating queue dynamics for reliability
- First to demonstrate TinyML feasibility for DRL in energy harvesting

4.6. Limitations and Future Work

4.6.1. Current Limitations

1. Simulation-based validation (physical deployment may reveal challenges)

2. Single-agent architecture (network-wide coordination could improve performance)
3. Fixed reward weights (adaptive weighting could improve flexibility)
4. LSTM prediction horizon (6-step may be insufficient for long-term planning)
5. Geographic limitation of solar data: The solar data was collected from Golden, Colorado (semi-arid climate), limiting generalizability to regions with different solar patterns (e.g tropical rainforests, foggy coastal cities, arctic zones). The DQN agent learns temporal patterns specific to this climate that may not hold elsewhere
6. Single-node focus with no routing consideration: The proposed framework optimizes energy management at the individual node level only. It does not account for multi-hop routing, cooperative energy sharing between nodes, or the additional energy overhead of packet forwarding in a true wireless sensor network deployment. This simplification may underestimate energy consumption in scenarios where nodes relay traffic for their neighbors.
7. Lack of hardware validation on real microcontrollers: Although the proposed DQN model is designed to be lightweight (~2,500 parameters) with the theoretical potential for TinyML deployment, all experiments were conducted on a high-performance computing setup (Intel i7, 32GB RAM, RTX 3060). No actual measurements on resource-constrained microcontrollers (e.g., ESP32 ARM Cortex-M) have been performed to verify inference time, memory footprint (RAM/Flash), or energy consumption during real-time operation. This remains an important step before claiming true suitability for resource-constrained devices.
8. The current implementation was evaluated in a workstation-based simulation environment. Future work will investigate TinyML deployment and inference benchmarking on low-power microcontrollers.

4.6.2. Future Work

Building on the limitations identified above, future research will focus on the following directions:

1. Multi-Node Cooperative Energy Management

Extend the proposed DQN framework to multi-hop WSNs by incorporating routing decisions into the state space (e.g., neighbor queue lengths, hop distance to gateway). Promising directions include: (i) multi-agent DRL where each node learns a distributed policy, and (ii) centralized DRL with graph neural networks (GNNs) to capture network topology for energy-aware routing in large-scale deployments.

2. Meta-Learning for Rapid Adaptation

Enable fast policy adaptation to new environments (e.g., different climates or harvesting conditions) with minimal retraining.

3. Hardware-in-the-Loop Testing

Validate the framework on physical microcontroller platforms (e.g., ESP32, ARM Cortex-M) to measure real inference time, memory footprint, and energy consumption.

4. Federated Learning for Privacy-Preserving Training

Enable distributed nodes to collaboratively learn policies without sharing raw data, preserving privacy while improving network-wide performance.

5. Conclusion

This paper presented an AI-driven framework that integrates hybrid energy harvesting (solar, vibration, thermal) with a Deep Q-Network (DQN) for energy management in wireless sensor networks. The energy allocation problem was formulated as a Markov Decision Process (MDP) with a state space comprising energy level, data queue size, and predicted harvesting rate. Experimental results demonstrate a 168% average improvement in network lifetime (reaching 300% in low-harvesting conditions) and 92% energy utilization efficiency (41.5% higher than static policies), outperforming static policies and existing DRL-based approaches. The inclusion of queue dynamics proved critical, reducing packet loss by 73% compared to queue-agnostic configurations. However, three key limitations must be acknowledged: (1) simulation-only validation, as physical deployment may introduce unmodeled constraints; (2) single-node focus with no routing or network coordination; and (3) geographic limitation of solar data to semi-arid climates, requiring retraining for regions like tropical rainforests or foggy coastal zones. For Green IoT deployments, the framework offers a computationally balanced solution with TinyML feasibility (~2,500 parameters). Future work will address multi-agent coordination, hardware-in-the-loop validation on microcontrollers (e.g ESP32, ARM Cortex-M), and adaptive reward weighting for greater flexibility.

Funding

The author declares that this research received no external funding.

Data Availability Statement

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

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Appendix

Detailed Algorithms

Algorithm A1: DQN-Based Energy Management

Initialize:

- Replay memory D with capacity N = 10,000
- Action-value network Q with random weights θ
- Target network $\hat{Q}$ with weights $\theta^- = \theta$
- Exploration rate $\varepsilon = 1.0$, $\varepsilon_{min} = 0.01$, $\varepsilon_{decay} = 0.995$
- Discount factor $\gamma = 0.95$, learning rate $\alpha = 0.001$
- Batch size B = 32, target update C = 100

For episode = 1 to M (M = 1000):

Initialize $S_1 = (E_1, Q_1, H_1)$

For t = 1 to T:

Select A_t: random (prob ε) or argmax $Q(S_t, a; \theta)$

Execute A_t, observe R_t, S_{t+1}

Store (S_t, A_t, R_t, S_{t+1}) in D

Sample mini-batch of B transitions

Compute targets: $y_j = R_j + \gamma \max \hat{Q}(S_{j+1}, a'; \theta^-)$

Update Q: minimize $L(\theta) = (1/B) \Sigma (y_j - Q(S_j, A_j; \theta))^2$

Update target: $\theta^- = \theta$ every C steps

$S_t = S_{t+1}$

$\varepsilon = \max(\varepsilon_{min}, \varepsilon * \varepsilon_{decay})$

Algorithm A2: Energy Harvesting Prediction (LSTM)

Input: 24 historical harvesting values [H_{t-24}...H_{t-1}]

Output: Predicted H_t for next time step

Architecture:

- LSTM layer: 32 units, tanh activation, dropout 0.2
- Dense output: 1 unit

Training: MSE loss, Adam optimizer, 50 epochs, 20% validation

Algorithm A3: Integrated System Workflow

At each 5-minute interval:

1. Measure E_t, Q_t, H_instant
2. Predict H_t using LSTM
3. Input $S_t = (E_t, Q_t, H_t_pred)$ to DQN → select A_t

4. Execute A_t (Transmit/Sleep/Sample)
5. Store experience and update DQN (training only)

Training Metrics:
Episode 0-100: Avg Reward = -15.2, Exploration ε = 0.95
Episode 101-300: Avg Reward = +8.7, Exploration ε = 0.61
Episode 301-500: Avg Reward = +24.3, Exploration ε = 0.37
Episode 501-700: Avg Reward = +31.8, Exploration ε = 0.22
Episode 701-1000: Avg Reward = +35.4, Exploration ε = 0.08
Convergence Time: ~400 episodes
Stability Achieved: Episode 600 onward