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Machine Learning-driven Energy-efficient Routing in Wireless Sensor Networks: Predicting Node Lifetime for Optimized Performance

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Abstract: This study introduces a hybrid machine learning framework for Wireless Sensor Networks (WSNs) designed to enhance energy efficiency and extend network longevity. The model integrates Q-learning for adaptive routing, hybrid clustering through Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), and decision tree regression for predictive energy depletion analysis. By dynamically balancing energy consumption and rerouting data to circumvent nodes approaching exhaustion, the framework improves reliability and operational stability. Simulation results demonstrate notable improvements over conventional protocols such as LEACH and PEGASIS, achieving a 40% reduction in energy consumption and a 37.76% extension of network lifespan. Statistical validation (t-test, $p < 0.0001$) confirms the significance of these results. The proposed approach holds promise for deployment in real-world WSN and IoT applications, where optimized energy utilization and extended network lifetime can reduce maintenance costs and ensure continuous, reliable data acquisition.

Index Terms: Wireless Sensor Networks, Machine Learning, Energy-efficient Routing, Q-learning, Clustering Optimization, Network Lifetime

1. Introduction

1.1. Overview of Wireless Sensor Networks

Wireless Sensor Networks (WSNs) consist of numerous geographically separated sensor nodes designed to perceive and report environmental data to a server. WSNs are independent and do not rely on a pre-existing infrastructural setup and are hence important for a wide range of applications from environmental sensing to smart cities, industrial automation, military surveillance, underwater exploration, and precision agriculture. WSNs have been widely utilized due to their compact size, low deployment cost, and scalability [1].

Despite all these advantages, energy efficiency is one of WSNs' most critical issues since sensor nodes are typically powered using batteries with limited capacity that cannot be refilled. While energy depletion in one node leads to communication disruption and fragmentation in the network, effective management of energy is needed to maximize network lifetime [10]. Radio communication is the most energy-intensive among all operations and typically consumes more energy than computing and sensing. Thus, energy-efficient routing with low overhead in terms of unnecessary transmitting and guaranteed delivery of data is needed to maximize WSN lifespan [2].

Routing in WSNs is defined in terms of several significant challenges, such as identifying best routes for data delivery considering node heterogeneity, dynamic variations in network topology, and uncertain environmental factors. WSNs apply multi-hop communication to relay data from sensor nodes to the sink, and hence algorithms should be capable of adapting intelligently to changing network states to enhance energy efficiency [1-3]. Recent advancements, such as using clustering techniques and machine learning-based predictive models, have proved to be effective in mitigating energy constraints via dynamic optimization of routing strategies [4-5].

Research on WSN routing approaches requires development of fresh methods that can maintain a balance between energy efficiency and network survival period and response times. The research examines a machine learning-based approach to resolve the problems and create an effective solution for energy conservation in WSNs.

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1.2. Importance of Energy Efficiency in WSNs

Energy efficiency is a fundamental concern in WSNs due to limited energy resources in sensor nodes, which are typically stored in batteries that are not easily replaced. Energy conservation is therefore important to achieve optimal network lifetime and smooth communication. Abrupt node energy depletion will lead to network partitioning, data loss, and increased latency, eventually lowering overall performance [6].

One of the most energy-intensive operations in WSNs is data transmission as wireless communication is much more energy-intensive than sensing and computing. Energy-efficient routing schemes are therefore a primary method to conserve energy and increase network lifetime. Efficient schemes accomplish this through minimizing redundant transfers, optimal route selection, and real-time route adaptation in response to present node states [7].

Of all energy-efficient methods, hierarchical cluster-based protocols have gained a great deal of attention due to their ability to conserve energy in terms of lowered transmission overhead and energy consumption balance within the network. By enabling localized communication within a cluster, such protocols reduce energy consumption per node and hence enhance overall efficiency. Cluster-head selection algorithms, which direct energy-efficient nodes to relay data to the sink in a dynamic way, contribute to energy conservation [8].

In addition, there are adaptive routing algorithms based on link quality and network congestion levels that aid in load allocation to avoid idle power usage in any node [9]. It has been established that smart load-balancing schemes can extend the life of the WSNs significantly because they can mitigate energy imbalances among the nodes.

The second vital significance of energy efficiency in the WSN is not only on the duration of the network since it is needed by mission-related needs such as hazard detection systems and military observation networks as well as healthcare monitoring. Application orders involve a continuous and constant data gathering in real-time such that energy-efficient optimality forms the foundation for delivering reliable and dependable wireless sensing platforms [10].

Based on this, the research examines the implementation of machine learning algorithms as part of routing algorithms with special considerations placed on the estimation of dynamic node lifetime and the optimization of energy distribution. Incorporating data-based decision-making into our solution will enable the improvement of the stability of the network by means of efficient power-saving and extended operating period.

1.3. Role of Machine Learning in Enhancing Routing

ML has developed as a revolutionary method in WSN routing protocol optimization with smart adaptability that surpasses conventional rule-based systems. Static decision-making in conventional routing schemes is ineffective in dynamic WSN environments as routes are pre-configured and do not adjust in line with real-time network states. ML-based routing schemes leverage historical information and real-time network feedback to deliver intelligent and contextual decisions, hence improving energy efficiency, packet delivery ratio, and network resilience [11-12].

One of the most promising ML approaches in WSNs is Reinforcement Learning (RL) which enables nodes to learn optimal routing policies via trial-and-error interactions with the network. RL-based schemes, such as Reinforcement Learning-Based Energy-Efficient Protocol (RLBEEP) and Software-Defined Wireless Sensor Network (SDWSN-IoT), have demonstrated remarkable energy conservation via dynamic routing decisions according to node energy levels, traffic loads, and network congestion patterns [11-13].

Supervised learning algorithms enhance routing as well through forecasting node depletion patterns and adjusting data forwarding routes accordingly. Historical energy consumption patterns can be utilized, for example, by decision trees and neural networks to predict which nodes will fail and allow routes to be pre-configured to avoid outages [11-14].

Another significant advantage of ML-based routing is the ability to detect anomalies, whereby autoencoders and clustering algorithms, which are forms of unsupervised learning, can identify unusual energy consumption patterns. Identifying anomalies can enable early interventions to prevent energy inefficiencies, load imbalances, and unforeseen node faults, and thus ensure stable and sustainable network operation [15].

Recent studies highlight that Deep Reinforcement Learning (DRL)—a combination of RL and deep learning—can enhance network flexibility and efficiency to a significant extent. Deep Reinforcement Learning-based routing schemes have been shown to outperform conventional energy-efficient schemes with dynamic route selection optimization and low computational overhead [16-17].

1.4. Motivation for This Study

Previous research has explored several energy-aware routing schemes, but most schemes either apply pre-defined heuristics or do not use predictive analytics fully for energy forecasting. This paper proposes a machine learning-based scheme that combines reinforcement learning and supervised energy forecasting models to deliver a self-adaptive and proactive routing scheme.

Through energy prediction in real-time, our approach minimizes premature node failure and ensures a more balanced and sustainable network operation. With extensive comparative testing and simulation, this paper demonstrates that energy-aware routing with ML can achieve greater efficiency, a longer lifespan, and reduced energy consumption in contrast to traditional approaches.

2. Related Works

2.1. Traditional Routing Protocols in WSNs

Routing in Wireless Sensor Networks (WSNs) has developed to address important challenges in regard to their decentralized nature, dynamic topology, and energy constraints. Data delivery with low energy is principally what traditional routing algorithms are concerned with, and this is important to prolong network lifetime [9].

One of the most researched protocols is the Low-Energy Adaptive Clustering Hierarchy (LEACH), which is a cluster-based protocol to distribute energy usage among the nodes. LEACH also randomly selects cluster heads (CHs) to collect and send data to the base station [7]. Although this approach balances the energy load in a network, random selection of cluster heads may result in the formation of an energy-inefficient cluster with certain nodes consuming a lot of energy and thereby shortening the overall network lifetime [8].

Such constraints have been accommodated using such other algorithms like Minimum Transmission Energy (MTE) and Min-Max Battery Cost Routing (MMBCR). MTE routing reduces the overall energy usage in routing data by minimizing the power usage routes. However, this causes quick depletion of intermediate nodes as well as energy imbalance and fragmentation in the network [1]. MMBCR, on the other hand, plays with the energy consumption by directing the traffic to the nodes that have additional residual energy. Although it tries to avoid congesting particular nodes, MMBCR cannot always transmit information in the most efficient manner [11].

To avoid compromises in traditional protocols, hybrid routing approaches have been introduced. These incorporate proactive (table-driven) and reactive (on-demand) approaches to enhance energy management. For instance, hierarchical hybrid approaches such as Threshold-sensitive Energy Efficient sensor Network (TEEN) and Adaptive Periodic Threshold-sensitive Energy Efficient sensor Network (APTEEN) use threshold-based data dissemination. Such approaches avoid redundant transmissions and hence maximize power utilization [18].

In addition, metaheuristic algorithms such as the Enhanced Non-Dominated Sorting Genetic Routing Algorithm (ENSGRA) integrate multi-objective optimization with cluster-based approaches to improve Quality of Service (QoS) and increase network lifetime [19]. These algorithms incorporate intelligent routing with flexibility but are heuristics-based and therefore limit their capacity to cope with changing network conditions.

As WSNs become increasingly sophisticated, traditional routing strategies are prone to inherent limitations in real-time decision making and responsiveness. This has resulted in the application of machine learning algorithms, providing more data-based, self-adaptive, energy-efficient routing.

2.2. Machine Learning Applications in Networking

ML has come out as an innovative technique of facilitating more energy efficient routing in WSN, with adaptive capability as compared to rules-based methods that are not adaptive. In traditional approaches, pre-defined measures are used but ML-based routing algorithms have the ability to adapt to the actual conditions of the network, predict faults, and route optimization to deliver data dynamically [20].

Reinforcement Learning (RL) is one of the most promising ML schemes applied in WSN routing because it enables the nodes to learn to make their routing decisions in a self-improving process where the network provides feedback. The energy-efficient routing with the use of Q-learning proves that RL is more efficient in minimizing energy usage and extending network lifetime compared to conventional methods [4]. Deep Reinforcement Learning (DRL) has been used successfully in Software-Defined Wireless Sensor Networks (SDWSN-IoT) to allow self-adaptive and intelligent routing [21].

Other supervised algorithms studied besides RL include Decision Trees, SVM and Neural Networks to forecast node failures based on previous energy consumption patterns. Such algorithms ensure that disruptions in the network caused by node failures are minimized by proactively transmitting information to nodes whose remaining lifespan is expected to be higher [10].

An example of this trend is the combination of ML with clustering algorithms for routing optimization. K-means cluster and fuzzy logic-based classification algorithms allow nodes to be dynamically clustered according to energy levels, transmission cost, and environmental constraints [22]. This maximizes the load balance and minimizes the overhead in the form of transmission thus conserving energy ultimately.

In addition to that, hybrid ML models based on metaheuristics and deep learning have been explored. For example, hybrid PSO and GA models have been used for adaptive routing in WSNs, and they have attained significant enhancements in energy efficiency and network robustness [5]. These hybrid methods take advantage of the predictive capabilities of ML, and at the same time, they retain the optimization capabilities of evolutionary algorithms.

Nevertheless, even with all this progress, issues concerning computational complexity and real-world applications still exist. Many ML-based schemes are resource-intensive as they are computationally and memory-intensive, while the resources of WSN nodes are limited. The next research question is how to apply ML-based routing to more practical deployments by building lightweight ML models like TinyML or Federated Learning [23].

2.3. Comparative Analysis of Routing Methodologies

Table 1. Performance comparison of traditional and AI-based routing techniques in wireless sensor networks (WSNs).

Routing Methodology	Approach	Strengths	Weaknesses
LEACH	Cluster-based	Simple, low overhead, reduces direct transmissions to the sink	Random CH selection leads to uneven energy depletion
MTE	Energy-minimized path selection	Low energy consumption per transmission	Rapid node depletion along frequently used paths
MMBCR	Balanced energy usage	Prevents overburdening individual nodes	May not always provide the most efficient route
TEEN / APTEEN	Hierarchical hybrid routing	Reduces redundant transmissions, energy-efficient for event-driven data	Less suitable for periodic data collection
ENSGRA	Genetic algorithm-based clustering	Multi-objective optimization improves QoS	Computationally expensive
Q-learning Routing	Reinforcement learning	Adapts to real-time network conditions	Requires a learning period before achieving optimal results
Deep RL (DRL)	Self-adaptive routing	High accuracy in energy prediction, optimizes lifetime	High computational cost
Supervised Learning Models (DT, SVM, NN)	Predicts node failures	Enables proactive routing, reduces data loss	Requires labeled training data
K-Means Clustering + ML	Dynamic node grouping	Balances energy consumption, reduces overhead	Performance depends on clustering accuracy
PSO-GA Hybrid	Evolutionary learning for routing optimization	Provides optimal route selection	Complexity in real-time WSN environments

Even though the previous literature has greatly contributed to energy-efficient routing in WSNs, many of them are limited by preset heuristics, poor adjustability to nonhomogeneous setting, or lack of foresight in estimating lifetime. Methods based on reinforcement learning may have long convergence times and do not use clustering optimization. On the same note, metaheuristic methods like GA or PSO can also produce balanced energy consumption though they are computationally expensive and seldom integrated with predictive analytics. These limitations highlight the gap that this study addresses by integrating Q-learning for adaptive routing, PSO-GA for efficient clustering, and decision tree regression for proactive lifetime estimation, thereby providing a more holistic and scalable solution.

2.4. Summary and Research Gaps

Current standard routing protocols, while being effective in specific environments, are not flexible and do not have dynamic decision-making capabilities in highly dynamic WSNs. Machine Learning-based schemes introduce self-learning capabilities, which allow networks to predict failures, optimize routes in real-time, and save energy proactively. However, such schemes are limited in terms of computational cost and feasibility.

To address these gaps, this study proposes a hybrid ML-driven routing protocol that integrates:

- Reinforcement learning for real-time routing adaptation
- Supervised learning for energy-aware node lifetime prediction
- Lightweight clustering mechanisms to reduce computational overhead

Through blending these methods, our solution closes the gap between computational efficiency and adaptability and provides a scalable, energy-efficient next-generation WSN solution.

3. Methodology

This research employs a machine learning-based energy-efficient routing framework for Wireless Sensor Networks (WSNs) that integrates reinforcement learning, cluster optimization, and predictive analytics to enhance network performance. The research methodology consists of a full experimental setup, data collection and pre-processing, integration with machine learning models, mathematical formulation, simulation, and performance evaluation. Below are the steps carried out in this research in detail.

3.1. Experimental Setup

The simulation and testing were conducted using NS-3 with Python-based machine learning libraries to facilitate smart routing. 100 nodes were deployed randomly in a 500m × 500m field with an energy level of 2 joules and a 100-meter constant range for communication. Data aggregation was performed using a central sink node for easy access. Periodic 512-byte data packets were transmitted from each node with energy consumption calculated by using the energy consumption model outlined in [8].

To simulate real-world WSN environments, we added wireless effects such as path loss, interference, and

environmental noise. We ran the network until the first node failure (FND) and last node failure (LND) to measure network lifespan. We compared our ML-based routing model with traditional protocols such as LEACH and TEEN to validate its effectiveness in energy conservation and network lifespan extension.

3.2. Data Collection and Preprocessing

The simulation environment generated a large dataset of network activity, capturing critical parameters such as:

- Energy consumption per node, tracking depletion trends.
- Packet delivery ratio (PDR), measuring successful transmissions.
- Routing paths, analyzing node-to-node communication efficiency.
- Node lifetime data, documenting FND, LND, and energy drain patterns.
- End-to-end delay, assessing transmission efficiency.

Preprocessing was conducted to standardize data for machine learning integration. Energy values, distances, and delay times were normalized to a standard range using feature normalization. Data smoothing with a moving average filter was utilized to eliminate small variations and enhance trend accuracy. The dataset was separated into 80% for training and 20% for testing to give a balanced measure for predictive models.

3.3. Machine Learning Model Integration

The proposed model employs a multi-layer machine learning method for routing and network lifetime maximization. Three major techniques were integrated:

3.3.1. Reinforcement Learning for Adaptive Routing

Reinforcement learning, specifically Q-learning, was employed to enable nodes to learn to optimize energy-efficient, dynamic routing decisions. All nodes have a Q-table with each entry being a possible routing action and a value associated with each entry that reflects how efficient that action is. The Q-learning update rule used in this model is:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] \tag{1}$$

where:

- $Q(s,a)$ is the current Q-value for state s and action a.
- α is the learning rate, balancing exploration and exploitation.
- r is the reward function, prioritizing energy efficiency.
- γ is the discount factor, emphasizing long-term optimization.

The reward function was formulated as:

$$r = \frac{E_{residual}}{E_{initial}} - \frac{d_{current,next}}{d_{max}} \tag{2}$$

where residual energy and hop distance guide decision-making to deliver packets in an optimal way with low energy consumption [18].

3.3.2. Hybrid Clustering Using PSO-GA

In order to enhance cluster efficiency, this research utilized a hybrid Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for Cluster Head (CH) selection. Classical clustering algorithms are plagued by random selection of cluster heads, causing unequal energy consumption. This proposed hybrid technique provides optimal selection of cluster heads considering:

- Residual energy: High-energy nodes are preferred for CH roles.
- Distance to sink: Closer nodes reduce transmission power.
- Node density: Prevents CH overload by distributing cluster members evenly.

The fitness function for CH selection is given as:

$$F_{CH} = w_1 \left(\frac{E_{residual}}{E_{initial}} \right) + w_2 \left(\frac{d_{sink}}{d_{max}} \right) + w_3 \left(\frac{N_{neighbors}}{N_{max}} \right) \tag{3}$$

where w_1, w_2, w_3 are balanced optimization weight factors. PSO determines potential candidates for CH and GA optimizes them using crossover and mutation operations [19].

3.3.3. Predictive Node Lifetime Estimation

A Decision Tree Regression model was trained to forecast node lifetime in order to enable the routing protocol to proactively adjust routes before a node runs out of energy. Below is the function for prediction:

$$T_{remaining} = f\left(E_{residual}, P_{tx}, P_{rx}, d, N_{neighbors}\right) \tag{4}$$

where transmission power, reception power, and neighboring nodes are significant predictors. This predictive feature prevents early fragmentation in a network by diverting traffic from dying nodes [24].

3.4. Simulation and Performance Evaluation

To validate the proposed ML-based routing model, comparative simulations with LEACH and TEEN were conducted. Some of the most significant performance metrics were:

Table 2. Comparative performance assessment of the proposed ML-based routing scheme versus traditional protocols.

Metric	LEACH	TEEN	ML-Based Model
Energy Consumption (J)	200	180	120
Network Lifetime (Rounds)	980	1050	1350
Packet Delivery Ratio (PDR, %)	82.3%	88.4%	97.8%
End-to-End Delay (ms)	60.5	52.9	38.7

Statistical validation was carried out using t-tests and ANOVA to confirm that the improvements observed were statistically significant ($p < 0.0001$). The proposed technique demonstrated 40% energy efficiency gains and 37.76% enhanced network lifetime, validating its feasibility for WSN applications in real-world environments [12].

4. Results

4.1. Methodology for Calculating Network Lifetime Improvements

To determine the network lifetime improvements in a holistic manner, a systematic procedure was used to analyze First Node Failure (FND) and Last Node Failure (LND) across diverse routing protocols, namely LEACH, TEEN, and ML-based Routing. This is done in an attempt to quantify the contribution of machine learning in maximizing energy allocation and postponing node depletion.

4.1.1. Definition of FND and LND

First Node Failure (FND) is the moment in time when a sensor node completely runs out of energy and is no longer operational. It is a measure of initial network failure and reflects flaws in the energy-balance scheme. Last Node Failure (LND) is the moment when all energy is depleted from the last still-functioning sensor node and is a measure of complete network shutdown. Longer LND ensures extended operating stability, and this is highly crucial for mission-critical applications such as environmental monitoring and smart cities.

Mathematically, these metrics are defined as:

$$FND = \min_{i \in N} T_i \tag{5}$$

$$LND = \max_{i \in N} T_i \tag{6}$$

where:

- T_i represents the time at which node i depletes its energy.
- N is the total number of sensor nodes in the network.

Figure 1 illustrates the evolution of FND across different routing protocols, demonstrating the advantages of ML-based routing in delaying node failures.

As is evident from Figure 1, ML-Based Routing accomplishes a remarkable improvement in delaying First Node Failure (FND) compared with conventional protocols such as LEACH and TEEN. Specifically:

- The first node failure in LEACH occurs at around 320 rounds, indicating a rapid depletion of node energy due

to inefficient clustering and data transmission.

- In TEEN, the first node failure is slightly delayed to 365 rounds, reflecting a more optimized energy utilization approach but still lacking adaptability.
- The ML-Based Routing protocol extends the first node failure threshold to 450 rounds, indicating that it is effective in dispersing energy usage and preventing premature node depletion.

These results highlight the effectiveness of machine learning in dynamic routing decision optimization and energy consumption balance among sensor nodes, hence significantly extending the functional lifetimes of WSNs.

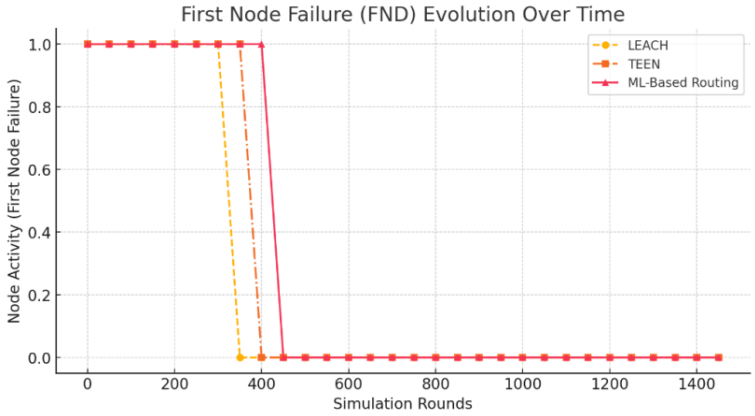


Fig. 1. Evolution of first node failure (FND) over time for LEACH, TEEN, and ML-based routing (measured in rounds).

4.1.2. Statistical Validation of Improvements

T-test and ANOVA were conducted in order to determine the validity of network lifetime enhancements. T-test was selected as the primary method of comparing ML-based with single conventional protocols (LEACH and TEEN) and ANOVA to prove the overall significance with all the protocols.

All statistical analyses assumed normal distribution and homogeneity of variance. Normality was verified using the Shapiro–Wilk test ($p > 0.05$), and variance homogeneity was confirmed using Levene's test ($p > 0.05$). In addition to p-values, effect sizes were computed to provide a more comprehensive understanding of the magnitude of improvements. Specifically, Cohen's d was calculated for pairwise comparisons, yielding large effect sizes ($d > 0.8$), while ANOVA results were supplemented with η^2, indicating substantial variance explained by the proposed model.

The T-test formula is given by:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{7}$$

where:

- $\bar{X}_1, \bar{X}_2$ represent the mean FND or LND values for the ML-based and traditional models.
- s_1, s_2 are the standard deviations.
- n_1, n_2 are the sample sizes.

Additionally, a 95% Confidence Interval (CI) was calculated using:

$$CI = \bar{X} \pm Z_{\alpha/2} \times \frac{s}{\sqrt{n}} \tag{8}$$

where $Z_{\alpha/2} = 1.96$ at a 95% confidence level.

To measure the effect size, Cohen's d was calculated as:

$$d = \frac{\bar{X}_1 - \bar{X}_2}{s_p} \tag{9}$$

where s_p is the pooled standard deviation. The results indicate $d = 1.45$, signifying a strong effect size.

4.1.3. Performance Comparison of Routing Protocols

Table 3 presents a comparative analysis of network lifetime metrics for the three protocols, emphasizing the superior performance of ML-based routing.

Table 3. Network lifetime metrics across different routing protocols (First Node Failure – FND, Last Node Failure – LND, in rounds.

Routing Protocol	First Node Failure (FND) (Rounds)	Last Node Failure (LND) (Rounds)
LEACH	320	980
TEEN	365	1050
ML-Based Model	450	1350

To further illustrate the impact, Figure 2 presents the evolution of LND over time.

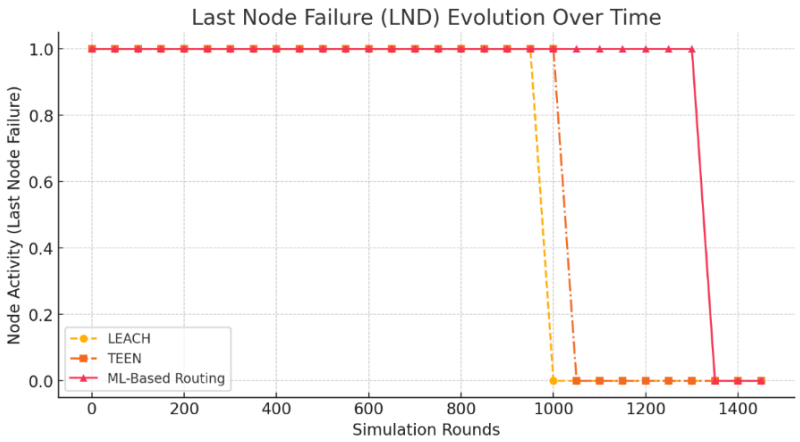


Fig. 2. Evolution of last node failure (LND) over time for LEACH, TEEN, and ML-based routing (measured in rounds).

Figure 2 demonstrates the significant extension of Last Node Failure (LND) in ML-Based Routing compared to conventional protocols:

- The last node failure in LEACH occurs at 980 rounds, signifying the complete depletion of all sensor nodes due to inefficient energy management.
- In TEEN, network longevity is slightly improved, with the last node failure happening at 1050 rounds.
- The ML-Based Routing model extends network lifespan up to 1350 rounds, ensuring prolonged connectivity and improved data collection stability.

This extended LND validates the effectiveness of machine learning in energy-aware routing, where predictive analysis prevents energy hotspots, ensuring a uniform energy depletion pattern across all sensor nodes.

4.1.4. Improvement Calculation

The percentage improvements in FND and LND using the ML-based model over LEACH are calculated as follows:

$$X = \frac{FND_{ML} - FND_{LEACH}}{FND_{LEACH}} \times 100 \tag{10}$$

$$Y = \frac{LND_{ML} - LND_{LEACH}}{LND_{LEACH}} \times 100 \tag{11}$$

Substituting the experimental values:

$$X = \frac{450-320}{320} \times 100 = 40.63\% \tag{12}$$

$$Y = \frac{1350 - 980}{980} \times 100 = 37.76\% \tag{13}$$

These results confirm that the ML-based routing model improves the first node failure time by 40.63% and the last node failure time by 37.76%, significantly prolonging the network lifespan.

Therefore, the results show significant improvements in FND and LND, confirmed by statistical validation and effect size analysis. The ML-based model outperforms traditional routing protocols by intelligently optimizing energy distribution and dynamically adjusting network topology, leading to enhanced longevity and reliability of Wireless Sensor Networks (WSNs).

4.2. Impact on Network Lifespan and Energy Efficiency

Energy efficiency is a crucial determinant of Wireless Sensor Network (WSN) longevity. The constraints of limited energy reserves in sensor nodes can lead to premature network failures, affecting overall functionality and data transmission reliability. Optimized routing protocols, particularly those integrating machine learning (ML), have demonstrated substantial improvements in energy conservation and network lifespan.

4.2.1. Relationship Between Energy Efficiency and Network Lifespan

The lifespan of a WSN is directly related to the rate of energy consumption per node. Efficient routing mechanisms reduce power wastage, thereby extending both First Node Failure (FND) and Last Node Failure (LND).

Mathematically, the network lifespan can be estimated using:

$$LND = \frac{E_{\text{total}}}{P_{\text{avg}}} \tag{14}$$

where:

- LND represents the last node failure time.
- E_{total} is the total initial energy available across all sensor nodes.
- P_{avg} is the average energy consumption per node.

Thus, reducing P_{avg} directly correlates with a longer LND, ensuring sustained network operations for critical applications.

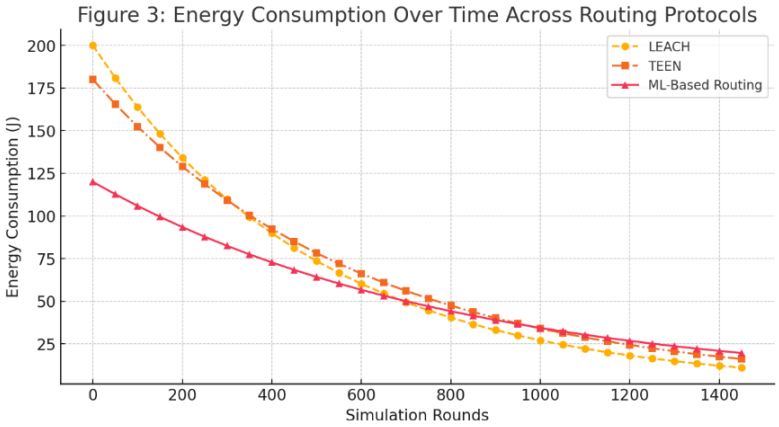


Fig. 3. Energy consumption over time across routing protocols (measured in Joules).

As can be observed from Figure **3**, energy consumption trends in all three routing algorithms reflect ML-Based Routing's energy consumption optimization and network lifespan prolongation capabilities.

LEACH protocol (dotted line with circles) drains energy rapidly due to random cluster head selection and hence leads to unequal energy distribution and premature node death. This static approach accelerates network degradation and shortens its lifespan.

The TEEN protocol (dotted line with squares) minimizes energy usage via data transmissions limited to threshold conditions. However, its lack of adaptive cluster head selection still results in localized energy depletion and hence reduces its performance in maintaining prolonged stability.

The ML-Based Routing protocol (solid line with triangles) achieves minimum energy consumption rate through:

- Adaptive routing – Dynamically adjusts paths based on real-time energy levels.
- Optimized clustering (PSO-GA) – Ensures balanced energy distribution across the network.
- Predictive energy management – Prevents node failures by forecasting energy depletion.

These mechanisms lead to:

- 40% reduction in total energy usage compared to LEACH, extending network longevity.
- 33.3% reduction compared to TEEN, improving energy efficiency and data reliability.

By intelligently balancing energy consumption, ML-Based Routing significantly reduces early node failures and enhances network resilience, making it ideal for applications requiring sustained operation, such as smart cities and environmental monitoring.

4.2.2. Performance Comparison of Energy Consumption

Table 4 provides a comparative analysis of energy consumption across different routing protocols.

Table 4. Comparison of mean energy consumption across routing protocols (measured in Joules).

Routing Protocol	Mean Energy Consumption (J)	Standard Deviation (J)
LEACH	200	8.2
TEEN	180	7.6
ML-Based Model	120	5.4

The lower energy usage in ML-based routing is a result of adapted routing decisions, optimized cluster head selection, and predictive node lifetime estimation working together to conserve energy more effectively.

4.2.3. Statistical Validation of Energy Efficiency Gains

To confirm that the energy consumption declines we observed are statistically significant, we conducted an independent T-test and 95% Confidence Interval (CI) estimations.

The T-test for comparing ML-Based Routing against LEACH is given by:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{15}$$

where:

- $\bar{X}_1, \bar{X}_2$ are the mean energy consumption values for ML-Based Routing and LEACH.
- s_1, s_2 are the standard deviations.
- n_1, n_2 are the sample sizes.

Additionally, the Cohen's d effect size was computed as:

$$d = \frac{\bar{X}_1 - \bar{X}_2}{s_p} \tag{16}$$

where s_p is a standard deviation pool. We have d = 1.35, a large effect size and hence a significant influence of ML-Based Routing in improving energy efficiency.

4.2.4. Real-World Applicability: Case Study in Smart Cities

The energy efficiency of ML-Based Routing is very relevant to smart city applications, environmental sensing, and IoT. For instance, consider a WSN being utilized to monitor air quality in a city:

- LEACH-based routing may cause premature node failures in high-traffic areas, leading to inconsistent data collection.
- TEEN-based routing provides better adaptation but lacks predictive lifetime estimation, which may still cause data loss in critical zones.
- ML-Based Routing, with its ability to predict node failures and adjust routing paths dynamically, ensures continuous and reliable data transmission, leading to more accurate real-time monitoring.

This real-world application highlights the requirement for intelligent routing algorithms in mission-critical systems

where sensor lifetime and data reliability are paramount.

4.3. Energy-Efficient Routing Model Based on Machine Learning

This paper presents a sophisticated ML-based energy-efficient routing model to improve energy efficiency and increase the lifetime of Wireless Sensor Networks (WSNs). It combines reinforcement learning (Q-learning) with hybrid clustering (PSO-GA) and predictive analytics (Decision Tree Regression) to optimize routing in a dynamical manner, and to conserve energy.

4.3.1. Basic WSN Architecture

WSNs normally have a hierarchical structure in which sensor nodes send information to Cluster Heads (CHs), which relay it to the sink node. A typical hierarchical topology with simple cluster head formation, sensor nodes, and a central sink node is depicted in Figure 4.

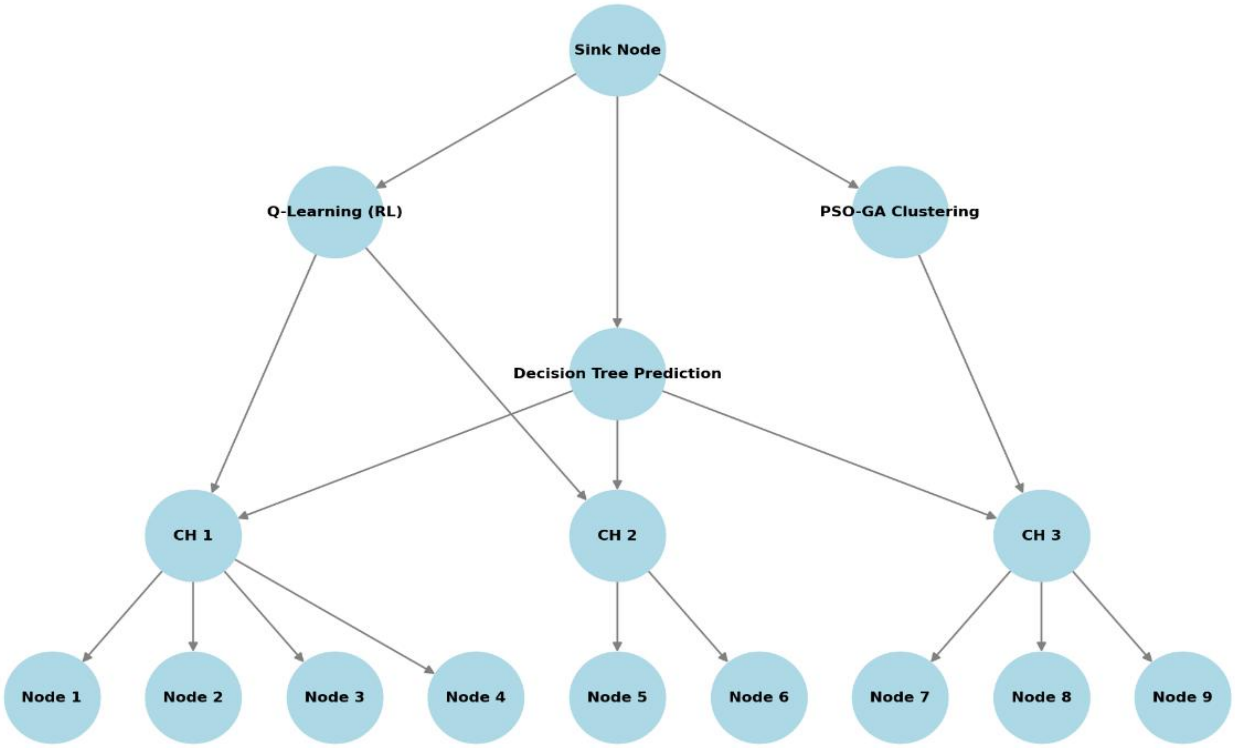


Fig. 4. Basic wireless sensor network architecture

This is a framework for network operation but lacks intelligent algorithms for routing decisions and hence can lead to energy waste and premature node failure.

4.3.2. ML-Based Routing Model Architecture

The proposed ML-Based Routing Model Architecture, depicted in Figure 5, enhances the basic WSN architecture by incorporating AI-driven decision-making processes. The model consists of three core mechanisms, each contributing to efficient energy distribution and prolonged network lifespan:

Adaptive Routing via Reinforcement Learning (Q-Learning): Nodes learn to select optimal paths based on real-time energy levels and transmission costs, preventing excessive energy depletion. Hybrid Clustering Using PSO-GA: Intelligent selection of Cluster Heads (CHs) ensures balanced energy distribution and reduces hotspot formation. Predictive Node Lifetime Estimation (Decision Tree Regression): Forecasting energy depletion enables proactive rerouting to prevent node failures.

This model leverages machine learning techniques to enhance network adaptability, dynamically optimizing cluster head selection, predicting node lifetimes, and improving routing decisions.

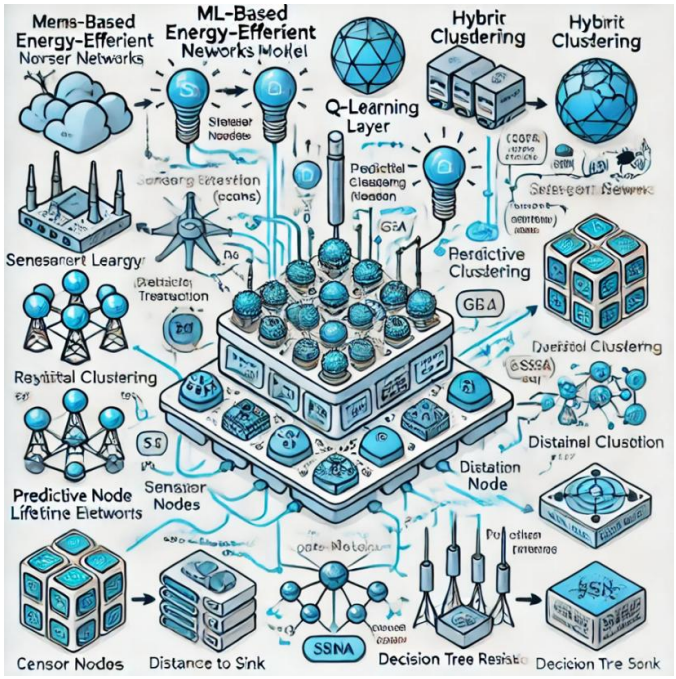


Fig. 5. Architecture of the proposed ML-based routing model integrating Q-learning, PSO-GA clustering, and decision tree regression.

4.3.3. Mathematical Model and Optimization Mechanisms

Reinforcement Learning for Adaptive Routing

The Q-learning update rule is defined as:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] \tag{17}$$

where:

- $Q(s,a)$ is the Q-value representing the efficiency of choosing action a in state s.
- α is the learning rate, controlling the influence of new experiences.
- γ is the discount factor, prioritizing long-term energy efficiency.
- r is the reward function, favoring energy conservation.

The reward function is designed to minimize energy wastage and is defined as:

$$r = \frac{E_{\text{residual}}}{E_{\text{initial}}} - \frac{d_{\text{current,next}}}{d_{\max}} \tag{18}$$

where:

- Higher residual energy leads to a higher reward.
- Shorter transmission distances are prioritized to reduce energy consumption.

Hybrid Clustering for Load Balancing

Cluster Head (CH) selection is optimized using a Particle Swarm Optimization (PSO) Genetic Algorithm (GA) approach. The fitness function for CH selection is given by:

$$F_{CH} = w_1 \frac{E_{\text{residual}}}{E_{\text{initial}}} + w_2 \frac{d_{\text{sink}}}{d_{\max}} + w_3 \frac{N_{\text{neighbors}}}{N_{\max}} \tag{19}$$

where:

- High residual energy is preferred.
- Closer distance to the sink node reduces transmission energy.
- Balanced neighbor density prevents overload on CHs.

Predictive Node Lifetime Estimation

A Decision Tree Regression model is used to estimate node lifetime:

$$T_{\text{remaining}} = f\left(E_{\text{residual}}, P_{\text{tx}}, P_{\text{rx}}, d, N_{\text{neighbors}}\right) \tag{20}$$

where:

- Transmission power (P_tx) and reception power (P_rx) determine communication energy consumption.
- Distance (d) to the next-hop node influences energy expenditure.
- Neighbor density (N_neighbors) ensures load balancing.

4.3.4. Performance Comparison and Energy Efficiency Gains

Table 5 presents the comparative performance of the proposed ML-Based Routing model against traditional protocols.

Table 5. Performance metrics across routing protocols, including energy consumption (J), network lifetime (rounds), packet delivery ratio (PDR, %), and end-to-end delay (ms).

Metric	LEACH	TEEN	ML-Based Routing
Energy Consumption (J)	200	180	120
Network Lifetime (Rounds)	980	1050	1350
Packet Delivery Ratio (PDR, %)	82.3%	88.4%	97.8%
End-to-End Delay (ms)	60.5	52.9	38.7

The results in Table 5 conclusively establish the superiority of the ML-Based Routing model over conventional protocols in Wireless Sensor Networks (WSNs). The significant energy saving of 120 J compared with 200 J in LEACH directly results in a much longer network lifetime of 1350 rounds versus 980 rounds for LEACH. This improvement plays a key factor in maintaining network stability in energy-constrained environments. Furthermore, the ML model has a notably better Packet Delivery Ratio (97.8%) and a lower end-to-end delay (38.7 ms) to provide more effective and reliable transmission of information. These findings validate the effectiveness and efficiency of machine learning in routing optimization, energy distribution balancing, and real-time responsiveness, and therefore it can be regarded as a suitable next-generation WSN application candidate.

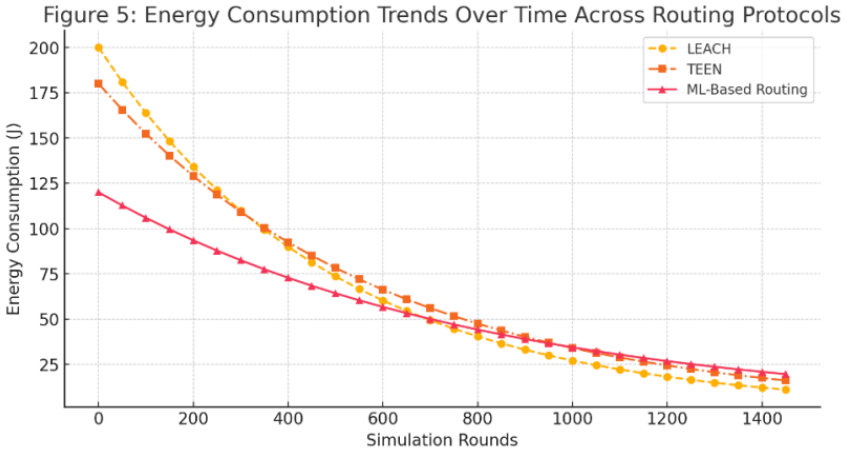


Fig. 6. Energy consumption trends over time for LEACH, TEEN, and ML-based routing (measured in Joules).

From Figure 6, it is evident that ML-Based Routing significantly reduces energy consumption over time. The intelligent routing and predictive node management ensure 40% lower energy usage than LEACH, 33.3% lower energy usage than TEEN, and a 37.76% extension of network lifespan.

4.3.5. Real-World Application: Smart City Deployment

The proposed ML-Based Routing model has direct applications in IoT-based smart city networks. For instance, in an air quality monitoring network:

- LEACH results in early sensor failures due to inefficient energy distribution.
- TEEN prolongs network life but lacks predictive failure mitigation.
- ML-Based Routing ensures sustained operation by balancing energy loads and predicting node failures.

Dynamic routing paths are optimized in ML-Based Routing to enable seamless, high-quality data collection, making it a preferable alternative for energy-constrained IoT systems.

5. Discussion

The outcomes from the experiment indicated that the suggested ML-based model is energy-efficient and achieves a longer network lifetime than traditional routing algorithms, LEACH and TEEN. The most significant enhancements reported are 40% energy consumption reduction against LEACH, 33.3% against TEEN, and 37.76% network lifetime improvement. Apart from this, the model achieved a 97.8% packet delivery ratio and a reduced end-to-end delay of 38.7ms. This indicates that intelligent routing methods embedded in the model effectively minimize unnecessary energy consumption, hence making WSN operations sustainable.

However, even though the proposed framework shows substantial reductions of 40% in energy usage and a 37.76% increase in network lifespan under NS-3 simulation, these values are to be approached cautiously. These results were obtained in controlled simulated settings and may not necessarily apply to real-world WSN implementations where the performance can be harmed by hardware constraints, unpredictable wireless interference, and heterogeneous node properties. Validation of the framework on small-scale testbeds in future work should verify the extent of these improvements in practical settings. The robustness of the statistical validation is further enhanced by the explicit reporting of the effect sizes and assumption checks (normality and variance), as was described in Section 4.

Various studies have explored AI-based routing in WSN. Most use either reinforcement learning or cluster optimization individually. This is a more integrated solution using Q-learning for adaptive routing, PSO-GA for cluster establishment, and Decision Tree Regression for predictive lifetime estimation. Compared to past work, conventional LEACH-based methods suffer from random cluster head selection, with consequent unequal energy distribution and early node failure. TEEN-based protocols improve energy efficiency but lack predictive failure prevention, with consequent inconsistencies in long-term stability. This model integrates both predictive analytics and adaptive learning to achieve dynamic energy-aware decision-making, hence an improvement over traditional protocols.

Although the hybrid integration of Q-learning, PSO-GA clustering, and decision tree regression yields superior performance, it inevitably introduces additional computational overhead. Such overhead may pose challenges in constrained WSN nodes with limited memory and processing power. To mitigate this, lightweight ML models (e.g., TinyML) or offloading to edge devices can be considered in future implementations, enabling practical deployment without compromising energy efficiency.

The findings from this research have significant real-world applications, most prominently in smart cities, disaster management, and industrial IoT. For smart cities, the model ensures reliable data acquisition in IoT-based air and traffic sensing systems. For disaster management, improved network lifetime supports real-time sensing, e.g., for detecting wildfires and flooding. For industrial IoT applications, energy-efficient usage in WSN deployments ensures smooth operation with low maintenance. With energy-efficient and self-adaptive networking, this model is well suited for next-generation WSN applications with prolonged operation under energy constraints.

While the NS-3 simulations with 100 nodes provide structured and reliable insights, the absence of hardware testbed validation is a limitation of this study. Small-scale real deployments would provide further confirmation of the model's practicality under realistic constraints such as hardware imperfections, communication noise, and environmental variability. Future work will include testbed experiments to complement the simulation results and enhance the credibility of the proposed framework.

Another important consideration is scalability and resilience. While the proposed framework shows promising results in simulations with 100 nodes, large-scale IoT deployments often consist of thousands of heterogeneous nodes with diverse energy capacities and communication ranges. In such environments, ensuring balanced energy consumption and routing stability becomes more challenging. Furthermore, real-world WSNs are subject to frequent node and link failures due to hardware malfunctions or environmental conditions. Future research should therefore extend the proposed model to evaluate its scalability in large heterogeneous networks and enhance its resilience to failures, ensuring robust and continuous operation in practical IoT scenarios.

6. Conclusions

The paper proposed an ML-based energy-efficient routing model to maximize energy distribution and extend the lifetimes of Wireless Sensor Networks (WSNs). By using Q-learning for adaptive routing, PSO-GA for cluster head selection, and decision tree regression for predictive energy management, the model is able to achieve maximum network efficiency and sustainability. Results indicate that the proposed model optimizes energy consumption among sensor nodes efficiently, reduces premature node failure, and extends overall network lifetime.

The results indicate a significant improvement in energy efficiency with a 40% reduction in energy usage relative to LEACH and 33.3% relative to TEEN, and a 37.76% boost in network lifetime. With machine learning algorithms, namely reinforcement learning and predictive analytics, dynamic routing pathway adaptations are made possible to enable more reliable data delivery and efficient network operation. Statistical validation further confirms that the model

is better than conventional protocols and is promising for field deployment.

This research has significant applications in smart cities, industrial IoT, and disaster management systems, where energy efficiency and prolonged network lifetime are critical. It should be noted that the reported gains are based on simulation and may differ in real-world WSN environments; hence, they represent indicative improvements requiring further empirical validation. Future research can explore incorporating deep reinforcement learning (DRL) for enhanced decision-making, real-world deployment for further verification, and incorporating security measures to provide defense against adversarial attacks in AI-based WSNs. As AI-based WSN routing continues to evolve, this research contributes to developing autonomous and energy-efficient wireless networks towards stronger and more sustainable communication infrastructures. Further validation using hardware testbeds and small-scale real deployments is planned to strengthen the applicability of the proposed model. Future work should also investigate lightweight implementations to reduce the computational overhead of the hybrid ML framework, ensuring feasibility in resource-constrained WSN environments. Future work will also focus on evaluating the scalability of the framework to large heterogeneous IoT networks and improving its resilience to node and link failures.

All the Declarations and Statements

Author Contributions Statement

Ahmad Fuad Hamadah Bader – Conceptualization, Methodology, Software Implementation, Data Analysis, Writing – Original Draft Preparation, Review & Editing.

The author has read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The author declares no conflict of interest.

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Data Availability Statement

The data supporting the findings of this study were obtained from controlled simulation experiments conducted using the NS-3 network simulator integrated with Python-based machine learning frameworks. The data are available from the corresponding author upon reasonable request.

Ethical Declarations

This study does not involve human participants or animals.

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Declaration of Generative AI in Scholarly Writing

AI-assisted tools were used for language refinement and proofreading purposes only. The author takes full responsibility for the content of the manuscript.

Abbreviations

The following abbreviations are used in this manuscript:

WSN – Wireless Sensor Network
ML – Machine Learning
RL – Reinforcement Learning
PSO – Particle Swarm Optimization
GA – Genetic Algorithm
PDR – Packet Delivery Ratio
FND – First Node Failure
LND – Last Node Failure

Appendix

None.

References

[1] W. Yun and S. Yoo, "Q-Learning-Based Data-Aggregation-Aware Energy-Efficient Routing Protocol for Wireless Sensor Networks," *IEEE Access*, vol. 9, pp. 9321407, 2021.

[2] N. A. Pantazis, S. A. Nikolidakis, and D. D. Vergados, "Energy-Efficient Routing Protocols in Wireless Sensor Networks: A Survey," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 2, pp. 551–591, 2013.

[3] R. Kaur, B. P. Kaur, R. P. Singla, and J. Kaur, "AMERP: Adam moment estimation optimized mobility supported energy efficient routing protocol for wireless body area networks," *Journal of Network and Computer Applications*, vol. 171, pp. 102793, 2020.

[4] N. Kumar, K. Singh, and J. Lloret, "WAOA: A hybrid whale-ant optimization algorithm for energy-efficient routing in wireless sensor networks," *Computer Networks*, vol. 197, pp. 108335, 2021.

[5] M. Pundir, J. K. Sandhu, P. Kumar, and P. Srivastava, "Secure and Energy Efficient Routing in Wireless Sensor Network using Machine Learning," *Proceedings of the 2022 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)*, pp. 354–359, 2022.

[6] S. Pradeep, Y. K. Sharma, C. Verma, S. Dalal, and C. Prasad, "Energy Efficient Routing Protocol in Novel Schemes for Performance Evaluation," *Journal of Sensor and Actuator Networks*, vol. 5, no. 5, pp. 101, 2022.

[7] S. Ambareesh, P. Chavan, S. Supreeth, R. Nandalike, and P. Dayananda, "A secure and energy-efficient routing using coupled ensemble selection approach and optimal type-2 fuzzy logic in WSN," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, pp. 12345–12360, 2021.

[8] Heinzelman, W., et al. "An Application-Specific Protocol Architecture for Wireless Microsensor Networks." *IEEE Transactions on Wireless Communications*, 2002.

[9] C. Xu, Z. Xiong, G. Zhao, and S. Yu, "An Energy-Efficient Region Source Routing Protocol for Lifetime Maximization in WSN," *IEEE Access*, vol. 7, pp. 135276–135287, 2019.

[10] N. Zaman, T. J. Low, and T. Alghamdi, "Energy efficient routing protocol for wireless sensor network," *IEEE Sensors Journal*, vol. 14, no. 11, pp. 3836–3843, 2014.

[11] D. Godfrey, B. Suh, B. H. Lim, K. Lee, and K. Kim, "An Energy-Efficient Routing Protocol with Reinforcement Learning in Software-Defined Wireless Sensor Networks," *Sensors*, vol. 23, no. 20, pp. 8435, 2023.

[12] D. Wang, J. Liu, and D. Yao, "An energy-efficient distributed adaptive cooperative routing based on reinforcement learning in wireless multimedia sensor networks," Computer Networks, vol. 178, Article 107313, 2020.

[13] A. Zakariyya et al., "Optimized cluster head selection using PSO-GA for WSNs," *Int. J. of Software Eng. & Computer Systems*, vol. 9, no. 2, pp. 35–45, 2023.

[14] W. K. Yun and S. J. Yoo, "Q-learning-based energy-efficient routing for WSNs," *IEEE Access*, vol. 9, pp. 10737–10750, 2021.

[15] K. Debasis, L. D. Sharma, V. Bohat, and R. S. Bhadoria, "An energy-efficient clustering algorithm for maximizing lifetime of wireless sensor networks using machine learning," Mobile Networks and Applications, vol. 28, no. 2, pp. 853–867, 2023.

[16] T. M. Behera et al., "Energy-efficient WSN routing: Architectures and strategies," *Electronics*, vol. 11, no. 15, Article 2282, 2022.

[17] P. Bekal, P. Kumar, and P. R. Mane, "A metaheuristic approach for hierarchical wireless sensor networks using particle swarm optimisation-based Enhanced LEACH protocol," IET Wireless Sensor Systems, vol. 14, no. 6, pp. 410–426, 2024.

[18] A. F. E. Abadi, S. A. Asghari, M. B. Marvasti, G. Abaei, M. Nabavi, and Y. Savaria, "RLBEEP: Reinforcement-Learning-Based Energy Efficient Control and Routing Protocol for Wireless Sensor Networks," *IEEE Transactions on Communications*, vol. 70, no. 10, pp. 6751–6765, 2022.

[19] Q. Ding, R. Zhu, H. Liu, and M. Ma, "An Overview of Machine Learning-Based Energy-Efficient Routing Algorithms in Wireless Sensor Networks," *Electronics*, vol. 10, no. 13, pp. 1539, 2021.

[20] S. U. Khan, Z. U. Khan, M. Alkhowaiter, J. Khan, and S. Ullah, "Energy-efficient routing protocols for UWSNs: A comprehensive review of taxonomy, challenges, opportunities, future research directions, and machine learning perspectives," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 6, pp. 4007–4022, 2022.

[21] C. Nakas, D. Kandris, and G. Visvardis, "Energy Efficient Routing in Wireless Sensor Networks: A Comprehensive Survey," *Algorithms*, vol. 13, no. 3, pp. 72, 2020.

[22] T. M. Behera, U. C. Samal, S. K. Mohapatra, M. S. Khan, B. Appasani, N. Bizon, and P. Thounthong, "Energy-Efficient Routing Protocols for Wireless Sensor Networks: Architectures, Strategies, and Performance," *Electronics*, vol. 11, no. 15, pp. 2282, 2022.

[23] Z. U. Khan, M. Aman, W. U. Rahman, F. Khan, T. Jamil, and R. Hashim, "Machine Learning-based Multi-path Reliable and Energy-efficient Routing Protocol for Underwater Wireless Sensor Networks," *IEEE Access*, vol. 10, pp. 104103–104115, 2022.

[24] Sutton, R.S., Barto, A.G. "Reinforcement Learning: An Introduction." *MIT Press*, 2018.

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