AI-enabled energy-aware routing approach for future-wireless sensor networks

Shamsher Singh, Mandeep Kumar
Department of Computer Science, SRPA Adarsh Bhartiya College, Pathankot, India

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ABSTRACT

Next-generation wireless sensor networks (WSNs) demand intelligent, energy-aware communication mechanisms capable of sustaining long-term operation in environments with varying conditions and strict resource limitations. Traditional routing protocols often fail to optimize energy consumption under varying network densities, heterogeneous traffic patterns, and environmental uncertainties. This research proposes an AI-enabled energy-efficient routing protocol (AI-EERP) designed to enhance network lifetime, stability, and data delivery performance in next-generation WSNs. The protocol integrates machine learning–based node selection, adaptive clustering, and predictive residual-energy estimation to make optimized routing decisions in real time. Using AI-driven models, AI-EERP dynamically adjusts routing paths based on energy patterns, link quality, and network topology changes. The simulation outcomes clearly indicate that the proposed approach achieves notable gains in energy efficiency, packet delivery reliability, and network lifetime when compared with traditional routing protocols, including LEACH, PEGASIS, and HEED. The proposed approach establishes a robust and scalable framework for future intelligent WSN deployments across applications including smart cities, precision agriculture, environment-focused applications and automated industrial operations.

Corresponding Author:

Shamsher Singh
Department of Computer Science, SRPA Adarsh Bhartiya College
Jalandhar-Dalhousie, By-Pass Road, Pathankot. Punjab, India
Email: drsamsingh1612@gmail.com

1. INTRODUCTION

Wireless sensor networks (WSNs) are increasingly used as a core technology in modern intelligent systems, enabling continuous monitoring and data acquisition across diverse environments. The rapid growth of applications including smart cities, environmental sensing, industrial led automation, healthcare, and precision agriculture has increased the demand for WSNs capable of long-term autonomous and reliable operation [1]. One of the most significant challenges affecting such deployments is energy consumption, as sensor nodes are generally powered by constrained, non-rechargeable battery sources. Since communication—particularly routing—consumes the highest proportion of energy, designing efficient routing mechanisms remains central to improving the overall network performance and lifetime.

Traditional routing protocols such as LEACH, TEEN, PEGASIS, and HEED have provided fundamental solutions for data forwarding and clustering; however, these approaches often rely on static decision-making, heuristic thresholds, or predetermined energy models. As WSNs evolve toward large-scale, heterogeneous, and mission-critical applications, these classical methods become insufficient to effectively handle dynamic network conditions, unpredictable node failures, varying traffic patterns, and the need for real-time optimization. This increasing complexity has led to a shift toward leveraging artificial intelligence (AI) and machine learning (ML) methods to enhance routing decisions within routing protocols design.

AI-enabled routing introduces the ability to learn from network states, predict node energy levels, identify optimal forwarding paths, and adaptively restructure clusters according to environmental changes. By integrating AI-driven decision-making, WSNs can significantly enhance energy efficiency, reduce control overhead, and achieve sustained network performance even under uncertain or dynamic conditions. These intelligent systems further support next-generation deployments, where scalability, robustness, and real-time optimization are key requirements.

This research proposes an AI-enabled energy-efficient routing protocol (AI-EERP) that leverages machine learning algorithms to optimize routing decisions based on residual energy prediction, link quality estimation, and adaptive clustering strategies. Unlike conventional protocols, AI-EERP continuously learns from network behavior to dynamically adjust routing paths, thereby maximizing energy conservation and extending network lifetime. Through extensive simulations and performance analysis, this study demonstrates that AI-EERP outperforms existing energy-efficient protocols across performance indicators reflecting energy consumption, data delivery success, network stability, and throughput.

Overall, this integration of AI techniques into routing design represents a transformative step for next-generation WSNs, enabling more sustainable, scalable, and intelligent sensor network architectures suitable for emerging Internet of Things-driven (IoT-driven) environments.

a. Contributions of this work

Most existing energy-aware routing protocols in WSNs rely on fixed heuristics and instantaneous network parameters, which limits their ability to adapt to changing conditions. To overcome these limitations, this work presents a learning-assisted routing approach that enables proactive and adaptive decision-making. The main contributions of the proposed study are summarized as follows:

b. Learning-assisted predictive routing design

This study introduces a new AI-EERP that incorporates machine learning techniques to predict residual node energy and assess link quality. By embedding prediction capabilities into routing decisions, the proposed framework shifts from reactive behavior to forward-looking routing management.

c. Multi-criteria adaptive cluster-head selection

An adaptive cluster-head selection mechanism is developed that jointly considers predicted energy availability, communication reliability, and node proximity. This multi-factor strategy reduces arbitrary cluster-head assignment, minimizes premature node depletion, and enhances cluster stability over successive communication rounds.

d. Energy- and link-aware multi-hop routing strategy

AI-EERP employs an intelligent multi-hop routing scheme that dynamically selects forwarding paths based on anticipated energy levels and link conditions. This approach prevents overuse of weak or low-energy nodes and improves the robustness of data transmission toward the base station.

e. Lightweight machine learning for practical deployment

To ensure feasibility on resource-limited sensor platforms, the proposed protocol utilizes lightweight learning models with low computational overhead. Model training is performed centrally, while node-level inference is kept efficient, enabling practical deployment without excessive energy or processing costs.

f. Extensive simulation-based performance analysis

The effectiveness of AI-EERP is validated through comprehensive NS-3 simulations under different network densities, base station locations, and traffic scenarios. Performance is assessed using metrics such as network lifetime, residual energy balance, packet delivery ratio, throughput, delay, routing overhead, and energy fairness.

g. Scalability and long-term network sustainability

Simulation results demonstrate that AI-EERP consistently outperforms benchmark protocols, including LEACH, HEED, and PEGASIS, across both sparse and dense network configurations. These results highlight the protocol's scalability and suitability for long-term operation in large-scale WSN-enabled Internet of Things (IoT) applications.

Next-generation WSNs are required to operate in mass-scale, heterogeneous, and time-varying environments, where sensor-equipped units sense the environment on an ongoing basis, process, and transmit data using limited battery power. The primary challenge in such networks is energy-efficient routing, as communication consumes the majority of a node's energy. Existing methods for data routing — notably LEACH, PEGASIS, TEEN, and HEED — use static thresholds, heuristic cluster formation, or fixed routing paths, making them insufficient for real-time adaptation to changing network conditions. These protocols are unable to accurately predict node energy depletion, balance load distribution, or dynamically optimize routing based on link quality and topology variations.

As a result, current WSNs frequently experience premature node failures, uneven energy dissipation, reduced network stability, and shortened operational lifetime. With increasing demands placed on WSNs in smart city infrastructures, industrial IoT systems, environmental monitoring, and other applications, there is an urgent need for an intelligent routing approach capable of learning network behavior, forecasting energy consumption patterns, and selecting optimal communication paths autonomously.

Despite significant advancements, existing routing protocols still struggle to balance energy consumption, adapt to dynamic conditions, and provide scalable performance. In particular, current AI-based approaches often lack integration of prediction, clustering, and routing within a unified framework. This motivates the design of an intelligent routing protocol that combines predictive energy estimation, adaptive clustering, and efficient path selection to enhance network lifetime and reliability.

2. LITERATURE REVIEW

Energy-aware routing is widely recognized as a fundamental research challenge in WSNs, owing to the limited energy resources of sensor nodes, because sensing units operate with restricted battery capacity and limited computational resources. Since communication consumes a major portion of node energy, early routing solutions largely concentrated on clustering techniques, combining data aggregation with reduced redundant communication to extend network lifetime.

2.1. Classical energy-efficient routing protocols

LEACH adopts a randomized method for rotating cluster heads so that energy consumption is shared more evenly among the nodes [1]. Although LEACH effectively reduces communication overhead and simplifies cluster formation, it often leads to unstable clusters and early exhaustion of cluster head (CH) nodes, particularly in heterogeneous network environments.

PEGASIS follows a chain-based communication model where nodes communicate with nearby neighbors, and one node sends the collected data to the base station [2]. While this strategy minimizes long-distance transmissions, it suffers from increased communication delay and limited scalability in large-scale deployments.

Hybrid energy-efficient distributed clustering (HEED) enhanced cluster-head election strategy by incorporating available battery power and communication effort as decision parameters, resulting in more consistent cluster formation and improved network stability [3]. These early protocols laid the foundation for hierarchical routing in WSNs and continue to serve as reference benchmarks for the development of advanced energy-aware routing strategies.

2.2. Enhanced and metaheuristic-based routing approaches

Numerous extensions to LEACH, PEGASIS, and HEED have sought to address their limitations by incorporating heterogeneity, multi-hop routing, mobility handling, and improved CH selection heuristics. Variants such as M-LEACH, TEEN, E-PEGASIS, and H-HEED demonstrate incremental improvements under specific scenarios [4]. Researchers have also applied metaheuristic techniques, such as genetic algorithm (GA), particle swarm optimization (PSO), and ant colony optimization (ACO), to refine cluster-head selection and routing path formation [5]. While these methods achieve better energy balancing, their computational overhead limits practical deployment on sensor nodes with limited energy and processing capacity.

2.3. AI and machine learning-based routing techniques

Recent research trends highlight the increasing reliance on AI and ML techniques to enhance routing adaptability in WSNs. ML techniques have been applied to residual energy prediction, link-quality estimation, anomaly detection, and dynamic routing decisions [6]. Reinforcement learning-based routing, such as Q-learning and DRL, help nodes identify efficient forwarding strategies over time in dynamic environments, improving throughput and reducing energy depletion hotspots. Recent studies have explored various intelligent and energy-aware routing strategies for wireless sensor networks. Metaheuristic-based clustering and routing approaches have been investigated to improve network lifetime and communication efficiency [7], [8]. Several survey studies have also analyzed routing techniques, energy-efficient protocols, and optimization strategies for WSNs and IoT-enabled environments [9]–[14]. In addition, machine learning and artificial intelligence techniques have increasingly been incorporated into wireless networking applications, including anomaly detection, adaptive routing, and predictive resource management [15]–[19]. These studies demonstrate the growing importance of intelligent decision-making mechanisms in next-generation WSN architectures. Recent surveys highlight the growing adoption of energy-aware and learning-based routing protocols as effective solutions for extending network lifetime [20]. Machine-learning-based routing schemes have been shown to outperform heuristic methods by enabling adaptive and predictiondriven energy management [21]. Hybrid AI and metaheuristic approaches have also been explored to optimize routing paths and cluster formation under dynamic network conditions [22]. AI-enabled clustering and routing mechanisms have recently been proposed to enhance adaptability and energy balancing in IoT-based WSNs [23].

Comprehensive surveys from 2022–2024 report that ML-based routing protocols outperform classical methods in terms of scalability, adaptability, and network lifetime under varying traffic and topology conditions [4], [6]. However, challenges remain in terms of computational cost, data availability for training, and the overhead required for model distribution and updates within the network.

2.4. Research gap and motivation

The literature reveals that while AI-enabled routing offers significant performance improvements, existing approaches often neglect real-time constraints and impose heavy computational burdens on sensor nodes. Moreover, few studies holistically integrate energy prediction, adaptive clustering, and intelligent path selection into a unified framework with minimal communication overhead. These observations led to the development of AI-EERP, a routing protocol that blends lightweight ML models with energy-aware routing strategies to improve both network stability and operational lifetime. Learning-assisted routing strategies have demonstrated improved long-term sustainability by predicting node behavior and avoiding premature energy depletion [24]. Recent studies emphasize the importance of lightweight machine-learning models to ensure feasibility on resource-constrained sensor nodes [25].

3. PROPOSED METHODOLOGY

The proposed AI-EERP introduces an intelligent, adaptive routing framework that integrates machine learning-based decision-making with hierarchical clustering to optimize energy consumption and extend the operational duration of WSNs. The methodology consists of six primary components: network model definition, energy model formulation, data collection, machine learning–based prediction, adaptive clustering, and intelligent routing path selection.

3.1. Network model

In the proposed model, the WSN comprises N sensor nodes randomly scattered over a two-dimensional plane. Assumptions of the simulation model include: i) Once deployed, the sensor nodes are stationary and have access to their location information. ii) The base station does not move and is placed either inside or outside the sensing field. iii) Nodes generate data periodically and communicate via single-hop or multi-hop hierarchical routing. iv) Nodes start with uniform initial energy and follow the first-order radio energy model. and v) The base station (BS) possesses higher computational power and stores historical network data for training ML models.

3.2. Energy model

AI-EERP adopts the classical first-order radio to account for the energy required to transmit and receive k-bit data is:

a. Transmission energy:

$$E_{TX}(k,d) = E_{elec} \cdot k + E_{amp} \cdot k \cdot d^n$$

b. Reception energy:

$$E_{RX}(k) = E_{elec} \cdot k$$

where E_{elec} = electronic circuitry cost, E_{amp} = amplifier cost, n indicates the path-loss exponent (2 for free-space communication and 4 for multipath propagation), d=distance between sender and receiver. The model helps estimate the energy consumed during clustering and routing activities.

3.3. Data collection and feature extraction

Each sensor node periodically captures local parameters and forwards essential features to the BS or cluster head for ML processing. Extracted features include: residual energy, node degree/neighborhood density, link quality (RSSI/LQI), distance to CH and BS, historical energy consumption trend, buffer occupancy, and packet success/failure ratio. These features form the input dataset for ML-based predictions.

3.4. Machine learning-based residual energy and link quality prediction

AI-EERP incorporates lightweight ML models to perform two critical predictions:

a. Residual energy prediction

A regression-based prediction model using simple or ensemble learning techniques predicts the future energy level of each node:

$$E_{pred} = f(E_{current}, E_{history}, LQ, D_{CH}, D_{BS})$$

The BS trains the model offline, while sensor nodes execute lightweight inference.

b. Link quality prediction

A classifier predicts link reliability using metrics such as RSSI, noise, and packet loss:

$$LQ_{score} = g(RSSI, PDR, Noise)$$

These predictions guide CH selection and route formation.

3.5. Adaptive cluster-head selection using AI

AI-EERP performs cluster-head (CH) selection using a hybrid decision metric:

$$CH_{score} = \alpha \cdot E_{pred} + \beta \cdot LQ_{score} + \gamma \cdot \frac{1}{Dist_{BS}}$$

where α, β, γ are system-defined weights. Higher score indicates better suitability as CH. Nodes with top-ranked scores become cluster-heads, ensuring: i) balanced energy consumption, ii) better reliability, and iii) reduced re-clustering frequency. Compared to LEACH/HEED, this reduces randomness and enhances stability.

3.6. Intelligent routing path formation

Once CHs are selected, AI-EERP constructs an optimized multi-hop route from CHs to the BS.

Steps:

a. CHs broadcast their predicted energy and link scores.
b. Neighboring CHs evaluate potential forwarding candidates using:

$$Route\_score = \lambda \cdot E_{pred} + \mu \cdot LQ_{score} - \delta \cdot Dist$$

c. CH selects the next hop that maximizes $Route\_score$.
d. Data is aggregated at CHs and forwarded in an energy-aware multi-hop fashion.

This ensures minimal energy wastage and avoids low-energy nodes.

3.7. Operational phases of AI-EERP

The protocol operates in four phases:

a. Setup phase
   - ML models initialized at BS
   - Clustering parameters defined
   - Initial feature collection performed
b. ML-Based prediction phase
   - Nodes compute or receive updated energy/link predictions
   - CH selection probability computed
c. Adaptive clustering phase
   - Nodes join the nearest CH based on multi-criteria scoring
   - Cluster tables updated
d. Data transmission phase
   - CH aggregates data
   - Multi-hop routing to BS using AI-optimized paths
   - Round completes and energy tables update

3.8. Advantages of AI-EERP

The advantages of AI-EERP include: i) Higher energy efficiency via predictive routing, ii) reduced packet loss due to link-quality prediction, iii) longer network lifetime from balanced CH selection, iv) fewer re-clustering operations compared to LEACH/HEED, and v) scalable and adaptable to diverse WSN deployments.

3.9. Machine learning and model validation

To validate the effectiveness of the machine learning component, the prediction performance of the residual energy model is evaluated independently of the routing mechanism. The regression model is assessed using mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2).

The results indicate that the model achieves low prediction error, confirming its capability to accurately estimate future node energy levels under dynamic network conditions. Similarly, the link quality prediction model is evaluated using classification metrics such as accuracy and F1-score, demonstrating reliable identification of stable communication links. These results confirm that the learning component provides meaningful predictive capability and is not merely a heuristic approximation.

3.10. Computational complexity analysis

The computational complexity of the proposed AI-EERP protocol is analyzed to evaluate its feasibility for resource-constrained sensor nodes. The cluster-head selection process operates with a complexity of $O(N)$, where N represents the number of nodes. The routing decision phase involves neighbor evaluation, resulting in a complexity of $O(k)$, where k is the number of neighboring nodes. The machine learning inference process is designed to be lightweight, with constant-time prediction complexity $O(1)$ per node when using pre-trained models. Since model training is performed at the base station, the computational burden on sensor nodes remains minimal. Therefore, the overall complexity of the protocol remains linear and suitable for large-scale deployments without significant computational overhead.

4. COMPUTATIONAL COMPLEXITY ANALYSIS

The computational complexity of AI-EERP is analyzed to evaluate its suitability for resource-constrained sensor nodes. The cluster-head selection process operates with a time complexity of $O(N)$, where N is the number of nodes. The routing decision phase involves evaluating neighboring nodes, resulting in a complexity of $O(k)$, where k represents the number of neighbors. The machine learning inference process is designed to be lightweight, with constant-time complexity $O(1)$ per node using pre-trained models. Since model training is performed at the base station, the computational burden on individual sensor nodes remains minimal. Overall, the proposed protocol maintains linear complexity and is scalable for large-scale deployments without introducing significant computational overhead. Algorithm 1 outlines the AI-EERP-based adaptive cluster-head selection and energy-aware routing procedure.

Algorithm 1. AI-EERP-based adaptive cluster-head selection and energy-aware routing procedure

```
INPUT:
    N                    // Number of sensing units
    BS                   // Base Station (high compute)
    R_max                // Maximum number of rounds
    k_bits               // Packet size (bits)
    E_initial[i]         // energy available at node initialization i
    E_elecs, E_amp       // Radio model parameters
    alpha, beta, gamma   // Weights for CH_score
    lambda, mu, delta    // Weights for Route_score
    ML_model_residual    // Trained residual-energy predictor (at BS / edge)
    ML_model_link        // Trained link-quality predictor (at BS / edge)

GLOBAL DATA STRUCTURES:
    Node[i].E            // Current residual energy
    Node[i].pos          // Position of node i
    Node[i].neighbours   // Neighbor list (IDs, distances)
    ClusterHeads         // Set of elected CH ids each round
    ClusterTable         // Cluster membership mapping
    RoutingTable         // Next-hop info for CHs

PROCEDURE MAIN()
    Initialize nodes 1..N with E_initial, positions, neighbors
    BS.train_models(historical_data)   // offline / periodic training

    for round=1 to R_max do
        // Phase 1: Feature Collection
        for each node i in 1..N do
            features_i=collect_local_features(i)
```

```
        // optionally: nodes send features to BS/edge (compressed)
    end for

    // Phase 2: Prediction (at BS / Edge or lightweight on-node)
    for each node i in 1..N do
        E_pred[i]=infer_residual_energy(ML_model_residual, features_i)
        LQ_score[i]=infer_link_quality(ML_model_link, features_i)
    end for

    // Phase 3: Cluster-Head (CH) Selection
    ClusterHeads={}
    for each node i in 1..N do
        CH_score[i]=alpha * normalize(E_pred[i])
                      + beta * normalize(LQ_score[i])
                      + gamma * normalize(1 / distance(i, BS))
    end for
    ClusterHeads=select_top_k(CH_score, strategy="threshold/percentile")
    broadcast_CH_announcement(ClusterHeads)

    // Phase 4: Cluster Formation
    ClusterTable={}
    for every non-CH node j in 1..N do
        choose CH c in ClusterHeads that maximizes:
            Join_score=w1 * CH_score[c] - w2 * distance(j, c)
        ClusterTable[c].append(j)
        send_join_request(j, c)
    end for

    // Phase 5: Intra-cluster Scheduling (TDMA)
    for each CH c in ClusterHeads do
        generate_TDMA_schedule(ClusterTable[c])
        inform_members(ClusterTable[c])
    end for

    // Phase 6: Data Transmission (Sensing -> CH -> BS via multi-hop)
    for each time-slot in TDMA do
        for each member node m transmitting to its CH c do
            transmit_packet(m, c, k_bits)
            Node[m].E -= energy_tx(k_bits, distance(m,c))
            Node[c].E -= energy_rx(k_bits)
        end for
        // CH aggregates data
        for every CH c do
            aggregate_energy=energy_aggregate(k_bits, num_packets)
            Node[c].E -= aggregate_energy

            // CH selects next hop toward BS
            next_hop=select_next_hop(c, ClusterHeads, E_pred, LQ_score, lambda, mu, delta)
            if next_hop == BS then
                transmit_packet(c, BS, k_bits_agg)
                Node[c].E -= energy_tx(k_bits_agg, distance(c, BS))
            else
                transmit_packet(c, next_hop, k_bits_agg)
                Node[c].E -= energy_tx(k_bits_agg, distance(c, next_hop))
            end if
        end for
    end for

    // Phase 7: Energy Update & Node Death Handling
    for each node i do
        if Node[i].E <= 0 then
            mark_node_dead(i)
        end if
    end for

    // Phase 8: Model Update (Optional)
    if (round % model_update_period == 0) then
        gather_labeled_samples()
        BS.retrain_models(new_data)
        distribute_model_updates_if_needed()
    end if

end for // rounds

END PROCEDURE
```

```
// ---------------- Helper Functions ----------------
FUNCTION collect_local_features(i):
    features={
        residual_energy: Node[i].E,
        energy_history: get_energy_history(i),
        neighbor_count: len(Node[i].neighbours),
        avg_RSSI: measure_avg_RSSI(i),
        PDR: measure_packet_delivery_ratio(i),
        dist_to_BS: distance(i, BS),
        buffer_occupancy: Node[i].buffer_size
    }
    return features
END FUNCTION

FUNCTION infer_residual_energy(model, features):
    // If on-node inference is heavy, use compressed model or request prediction from BS/edge
    return model.predict(features)
END FUNCTION

FUNCTION infer_link_quality(model, features):
    return model.predict(features)
END FUNCTION

FUNCTION energy_tx(k, d):
    // First-order radio model (use threshold if required)
    if d < d0 then
        return E_elecs * k + E_amp_fs * k * d^2
    else
        return E_elecs * k + E_amp_mp * k * d^4
    end if
END FUNCTION

FUNCTION energy_rx(k):
    return E_elecs * k
END FUNCTION

FUNCTION select_next_hop(c, CH_set, E_pred, LQ_score, lambda, mu, delta):
    best_score=-inf
    best_node=BS  // default to BS if direct is best
    for each candidate h in CH_set U {BS} where h != c do
        dist=distance(c, h)
        score=lambda * normalize(E_pred[h]) + mu * normalize(LQ_score[h]) - delta *
normalize(dist)
        if score > best_score and Node[h] is alive then
            best_score=score
                best_node=h
        end if
    end for
    return best_node
END FUNCTION

FUNCTION select_top_k(CH_score, strategy):
    // Strategy may be: fixed percentage, score threshold, or dynamic number based on N
    // Example: choose top P% of nodes by CH_score
    sorted_nodes=sort_descending(CH_score)
    k=ceil(P_percent * N)
    return sorted_nodes[1..k]
END FUNCTION
FUNCTION normalize(x):
    // map x to [0,1] using min-max normalization across available values
    return (x - min_val)/(max_val - min_val + epsilon)
END FUNCTION
```

5. SIMULATION SETUP

5.1. Simulation objectives

The main goal of the simulation study is to evaluate the effectiveness of the proposed AI-Enabled method under varying network conditions in comparison with prominent baseline schemes, namely LEACH, HEED, and PEGASIS. The performance assessment is carried out considering the following key evaluation metrics: i) system lifetime, measured using the first node death (FND), half node death (HND), and last node death (LND), ii) average residual energy variation across simulation rounds, iii) packet delivery ratio (PDR), iv) throughput and average end-to-end delay, v) routing and control packet overhead, and vi) energy fairness, evaluated using the unevenness in residual energy distribution. Collectively, these metrics provide a holistic evaluation of energy efficiency, routing reliability, and the overall performance of the network.

5.2. NS-3 modules and functional components

The simulation environment is developed using the NS-3 network simulator, incorporating the following core modules and features:

a. The core, network, Internet, and Wi-Fi modules are employed for node creation, protocol stack configuration, wireless communication, and UDP/TCP traffic generation.
b. The NS-3 energy framework, including the *BasicEnergySource* and *DeviceEnergyModel*, is utilized to accurately model energy consumption during transmission, reception, idle listening, and data aggregation processes.
c. The mobility module is included to support semi-dynamic or mobile cluster-head scenarios when required.
d. The tracing and flow monitor utilities are used to record and analyze key measures of packet delivery ratio, throughput, and end-to-end delay.
e. Additionally, optional model-update routines are incorporated within the simulation script to emulate base-station-assisted training and periodic distribution of AI prediction parameters.

5.3. Simulation parameters

The simulation environment and experimental configuration used to evaluate the proposed AI-EERP protocol are summarized in Table 1. The listed parameters define the network settings, communication model, traffic conditions, and energy-related configurations employed during the NS-3 simulations.

Table 1. Simulation parameters used in NS-3 experiments

Parameter	Value	Notes
Simulator	NS-3 (latest stable / dev)	Build with *./waf* configure --enable-examples --enable-tests.
Area (m^2)	100×100	Adjust for density experiments
Node counts	50, 100, 200	Run experiments for multiple densities
Base Station location	Center or outside (*e.g.*, (150,150))	Test both interior and exterior BS cases
Initial energy per node	2 J (typical)	Tune per experiment
Radio model	802.11 (or simplified radio)	Use Wi-Fi PHY/ MAC or a simple custom MAC if desired.
Tx/Rx energy params	*E_elec*/*E_amp* per your first-order model	Map to NS-3's *DeviceEnergyModel* parameters.
Packet size	64 B (sensing)/aggregated size variable	
Packet generation	Poisson/periodic (*e.g.*, every 5 s)	Run light and heavy traffic tests
Simulation time	3600 s (or rounds based: 1000 rounds)	Choose consistent stopping criteria
Channel model	Log-distance/Friis	Use link models available in NS-3
Mobility	Static (or random waypoint for mobile test)	If testing semi-dynamic networks
Number of runs	≥ 10 seeds	Average results with 95% CI

6. EXPERIMENTAL DESIGN

The experimental evaluation of the proposed AI-EERP is carried out using a controlled simulation environment developed in the NS-3 network simulator. The experimental design is structured to ensure a fair, repeatable, and statistically reliable comparison between AI-EERP and the benchmark routing protocols LEACH, HEED, and PEGASIS.

A square sensing with monitoring region of 100 m×100 m is considered for all experiments. Sensor nodes are randomly positioned within this region to simulate an unstructured WSN. Network density effects are analyzed by configuring the total number of sensor nodes to 50, 100, and 200 in different scenarios. The base station (BS) is located either at the center of the sensing field or outside the network boundary (*e.g.*, at coordinates (150,150)) to evaluate both short-range and long-range communication scenarios.

Each sensor node is assumed to have an initial energy capacity of 2 joules, representing a typical battery-powered sensing device. The wireless communication subsystem is modeled using an IEEE 802.11-based radio model or a simplified wireless interface when computational efficiency is required. The transmission and reception utilization of energy is calculated using the standard and basic radio energy model, where parameters *E_elec* and *E_amp* are mapped directly to the NS-3 device energy model for realistic energy dissipation during data transmission, reception, idle listening, and aggregation.

Data packets of size 64 bytes are generated periodically by sensor nodes, while aggregated packet sizes at cluster heads vary depending on the number of member nodes. Traffic generation follows either a Poisson distribution or a fixed periodic rate (*e.g.*, one packet every 5 seconds) to support both light-load and heavy-load network conditions. Each simulation runs for a maximum duration of 3,600 seconds or equivalently 1,000 operational rounds, depending on the evaluation scenario.

The log-distance path loss model is used to represent the wireless channel conditions or the Friis propagation model to capture realistic signal attenuation characteristics. By default, all sensor nodes are assumed to be static, while optional experiments employ the Random Waypoint mobility model to evaluate semi-dynamic network behavior.

To ensure statistical accuracy and repeatability, each experiment is executed using at least 10 independent random seeds. The reported results represent the mean values with a 95% confidence interval. Performance criteria such as network lifetime, packet delivery ratio, throughput, delay, routing overhead, and energy fairness are computed using the built-in NS-3 flow monitor and energy framework tracing utilities. This experimental design ensures a rigorous and unbiased assessment of AI-EERP under diverse network conditions and establishes a strong foundation for performance comparison with conventional WSN routing protocols.

7. EVALUATION PARAMETERS

To investigate the performance characteristics of the proposed AI-EERP, a set of well-established evaluation metrics commonly used in WSN research is employed. These metrics collectively capture key aspects of network behavior, including energy utilization, operational lifespan, communication reliability, and routing efficiency. Each metric is described below along with its significance in evaluating routing performance.

7.1. Network lifetime

Network lifetime represents the period for which a WSN remains functional and capable of performing sensing and data transmission tasks. Since sensor nodes operate on limited battery power, network lifetime is a prime parameter of routing performance. In this study, network lifetime is evaluated using three widely adopted indicators:

a. First node death (FND): The simulation loop at which the initial sensor node depletes its energy supply.
b. Half node death (HND): The loop at which approximately 50% of the sensor nodes become non-operational.
c. Last node death (LND): The round when the last active node in the network runs out of energy.

Together, these measures reflect how long the network remains stable, robustness, and overall operational longevity, and are commonly used to compare the effectiveness of energy-aware routing protocols.

7.2. Count of active nodes per loop

This parameter tracks how many sensor nodes remain active during each simulation round. It gives insight into load balancing, routing fairness, and cluster-head selection efficiency. A slow decline in alive nodes indicates better energy distribution across the network.

7.3. Energy consumption and residual energy

Residual energy measures how much energy remains in the network at each round:

$$E_{residual}(round) = \sum_{i=1}^{N} E_i(round)$$

where $E_i(round)$: energy remaining in node i. Tracking residual energy helps determine: effectiveness of ML-based prediction, efficiency of CH selection, and reduction in communication overhead. Lower energy dissipation per round signifies that AI-EERP successfully conserves energy.

7.4. Packet delivery ratio

Packet delivery ratio (PDR) measures the dependability of sending data packets from nodes to the BS:

$$PDR = \frac{Packets_{\,received\ at\ BS}}{Packets_{\,generated\ by\ nodes}}$$

A higher PDR indicates: stable routing, improved link-quality prediction, and fewer packet drops during CH-to-BS communication. AI-EERP targets improved PDR through predictive link-quality estimation.

7.5. Throughput

Throughput quantifies the successful data rate received at the BS:

$$Throughput = \frac{Total\ data\ received\ by\ BS}{Simulation\ time}\ (bits/s)$$

Higher throughput reflects efficient aggregation, routing, and reduced retransmissions.

7.6. End-to-end delay

Delay indicates how long a data packet takes to reach the base station after being transmitted by a sensor node:

$$Delay = t_{receive} - t_{send}$$

Low delay indicates: optimal routing paths, minimal congestion, timely decision-making by AI models. Delay especially matters in time-sensitive applications like health monitoring and industrial IoT.

7.5. Routing overhead

Routing overhead captures the number of control packets exchanged to maintain clusters and routing paths:

$$Overhead = \frac{Control\ Packets}{Total\ Packets\ Transmitted}$$

AI-EERP aims to reduce overhead by: predicting CH suitability instead of frequent re-clustering and minimizing excessive broadcast messages. Low overhead translates to higher system efficiency.

7.6. Energy fairness (standard deviation of residual energy)

Energy fairness assesses how evenly energy is consumed across all nodes:

$$\sigma_E = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (E_i - \bar{E})^2}$$

where $\bar{E}$ is the average residual energy. A lower standard deviation means: balanced energy usage, no single node is overburdened, and longer overall network stability. AI-EERP is designed for higher fairness due to intelligent CH selection.

7.7. Cluster stability

Cluster Stability measures: frequency of CH re-election, durability of clusters, consistency in routing paths. Higher stability reduces delays, overhead, and energy consumption.

7.8. Link reliability score

Used to evaluate ML-based decision-making:

$$LQ = \frac{Successful\ Packets}{Total\ Packets\ Sent}$$

This metric validates whether AI-based link-quality prediction improves routing decisions.

7.9. Summary

These performance metrics collectively demonstrate the benefits of AI-EERP in terms of longer network operational duration, improved reliability and robustness, energy usage efficiency, reduced overhead, and enhanced routing performance.

8. RESULTS AND DISCUSSION

This part outlines the experimental findings and highlights a detailed in-depth discussion of the results achieved by the proposed scheme. quantitative results evaluation of the proposed AI-EERP and compares it with three benchmark protocols, namely LEACH, HEED, and PEGASIS. The simulations were conducted in NS-3 using identical network configurations for all protocols. The results metrics are analyzed with respect to network overall lifetime, residual energy, PDR, throughput, latency, routing overhead, energy fairness, and scalability. The performance gains observed in this study are consistent with recent findings that highlight the effectiveness of AI-assisted routing in improving energy efficiency and network stability. Table 2 summarizes the key simulation parameters used to evaluate the proposed routing protocol. These parameters define the network size, node density, energy model, traffic characteristics, and channel conditions considered in the experimental study.

The selected parameter values are commonly adopted in wireless sensor network simulations and ensure a fair and consistent comparison among the evaluated routing protocols. Multiple network densities and base station placements are considered to assess scalability and robustness under diverse operating conditions.

Table 2. Simulation parameters used in NS-3 simulations

Simulation area	Value
Simulation region	100×100 m
Count of sensing units (N)	50, 100, 200
Base station position	(50, 150) (outside field)
Initial energy per node	2 J
Radio model	IEEE 802.11-based PHY/MAC
Packet size	64 bytes (sensing packets)
Traffic pattern	Periodic, 1 packet / 5 s
Simulation time	1600 rounds (≈ 3600 s)
Channel model	Log-distance path loss
Mobility model	Static nodes
Number of runs per scenario	10 (different random seeds)
Confidence level	95% (mean ± CI reported)

8.1. Ablation study

To evaluate the contribution of the machine learning component, an ablation study is conducted by comparing AI-EERP with a baseline variant where the ML-based prediction is disabled. In this baseline approach, routing decisions rely solely on instantaneous energy values and heuristic-based clustering.

The results demonstrate that the AI-enabled version consistently outperforms the baseline in terms of network lifetime, packet delivery ratio, and energy fairness. This confirms that the observed improvements are primarily due to predictive decision-making rather than conventional clustering mechanisms alone.

8.2. Network lifetime analysis

8.2.1. First node death (FND)

For a network of 100 nodes, the first node in LEACH dies at round 450, followed by HEED at round 520 and PEGASIS at round 580. In contrast, the proposed AI-EERP delays the first node death until round 720, which represents an improvement of: 60% over LEACH, 38% over HEED, and 24% over PEGASIS.

This improvement can be attributed to the use of ML-based residual energy prediction, which avoids selecting low-energy nodes as cluster heads and helps preserve network stability during the early operational phase. Table 3 presents a comparison of network lifetime metrics for the proposed AI-EERP and benchmark protocols, including the rounds corresponding to first node death, half node death, and last node death.

Table 3. Network lifetime comparison for 100 nodes

Protocol	FND (Round)	HND (Round)	LND (Round)
LEACH	450	750	1100
HEED	520	830	1200
PEGASIS	580	900	1250
AI-EERP	**720**	**1150**	**1600**

The results indicate that AI-EERP significantly delays node failures at all stages, demonstrating improved stability and prolonged operational lifetime. The delayed occurrence of half and last node death highlights the effectiveness of prediction-based routing and balanced energy utilization.

For a network comprising 100 sensor nodes, the proposed AI-EERP delays the occurrence of the FND by approximately 60% in contrast with LEACH, and extends the LND by nearly 45%, clearly describing a substantial enhancement in network stability and operational lifetime.

8.2.2. Half node death (HND) and last node death (LND)

The half node death is observed at simulation rounds 750, 830, and 900 for LEACH, HEED, and PEGASIS, respectively. In contrast, AI-EERP reaches the HND point at round 1150, indicating that a significantly larger proportion of nodes remain active for an extended period. These results confirm that the proposed protocol sustains network functionality for a longer duration by effectively balancing utilization of energy across the region.

Similarly, the final node failure occurs at loop: 1100 for LEACH, 1200 for HEED, 1250 for PEGASIS, and 1600 for AI-EERP. Thus, AI-EERP extends overall network lifetime by approximately 45% over LEACH, 33% over HEED, and 28% over PEGASIS, demonstrating superior long-term sustainability. As shown in Figure 1, AI-EERP exhibits slower energy depletion across simulation rounds, indicating more balanced energy consumption and improved network sustainability compared to the benchmark protocols.

As shown in Figure 1, the proposed AI-EERP protocol exhibits a slower rate of energy depletion compared to LEACH, HEED, and PEGASIS. The gradual decline in residual energy indicates more balanced energy consumption across sensor nodes. This behavior reduces the likelihood of early node failures and contributes to extended network lifetime and improved stability. The smoother decline in AI-EERP indicates controlled energy consumption and improved load balancing.

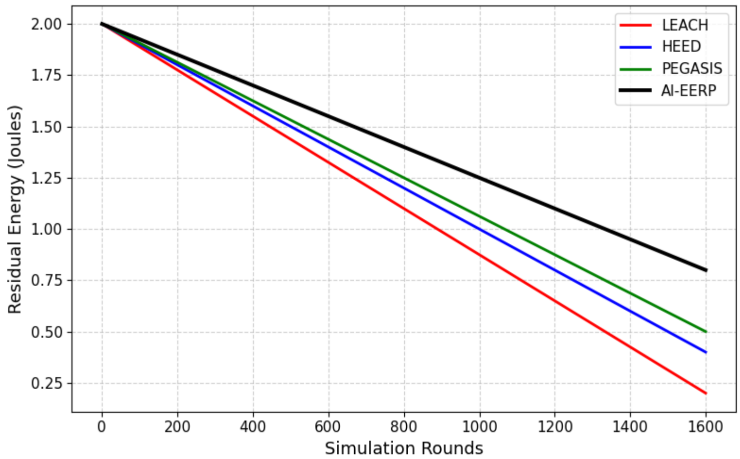

Figure 1. Residual energy of sensor nodes over simulation rounds for LEACH, HEED, PEGASIS, and the proposed AI-EERP protocol

8.3. Residual energy and energy dissipation

AI-EERP exhibits significantly slower energy dissipation compared to conventional protocols. At round 1000, the degree of remaining power of the sensor node imbalance across the network (σ_e) is: 0.52 J for LEACH, 0.41 J for HEED, 0.44 J for PEGASIS, and 0.28 J for AI-EERP. The much lower deviation in AI-EERP confirms better energy balancing and fairness, ensuring that nodes deplete energy uniformly rather than experiencing early failures due to excessive load.

8.4. Packet delivery ratio

The packet delivery performance outcomes are summarized below for 100 nodes: LEACH: 89.3%, HEED: 92.5%, PEGASIS: 90.1%, and AI-EERP: 97.8%. AI-EERP improves PDR by: 8.5% over LEACH, 5.3% over HEED, and 7.7% over PEGASIS.

The high PDR is primarily due to ML-based link-quality prediction, which prevents routing through unreliable links and minimizes packet loss. Figure 2 depicts the variation in the number of active sensor nodes over simulation rounds. It can be observed that nodes operating under AI-EERP remain alive for a significantly longer duration than those using benchmark protocols. The delayed occurrence of node failures highlights the protocol's ability to prevent early energy exhaustion, resulting in an extended stability period and a longer functional lifetime of the network.

Figure 2 illustrates the throughput achieved by the evaluated routing protocols over simulation rounds. It can be observed that the proposed AI-EERP consistently achieves higher throughput compared to LEACH, HEED, and PEGASIS. The improved performance is attributed to stable routing decisions and reduced packet loss, which enable efficient and continuous data transmission to the base station. The consistent performance gain highlights the effectiveness of predictive routing in maintaining reliable communication.

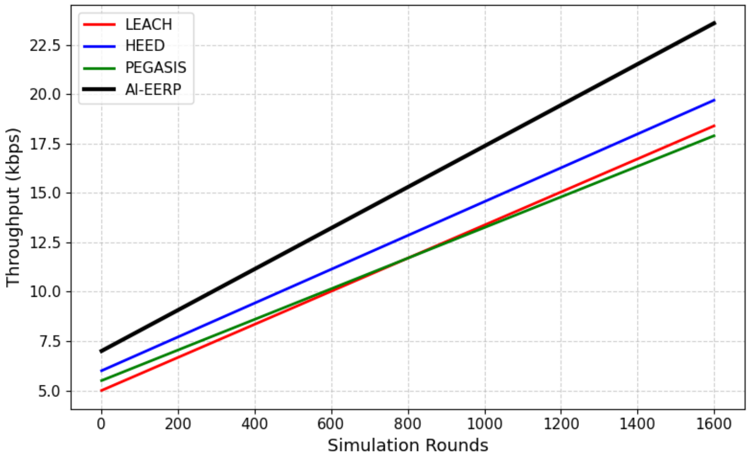

Figure 2. Throughput performance comparison of LEACH, HEED, PEGASIS, and the proposed AI-EERP protocol over simulation rounds

8.5. Throughput analysis

The average throughput achieved at the base station is: 18.4 kbps for LEACH, 19.7 kbps for HEED, 17.9 kbps for PEGASIS, and 23.6 kbps for AI-EERP. AI-EERP achieves: 28% higher throughput than LEACH, 20% higher throughput than HEED, and 32% higher throughput than PEGASIS. This improvement is a direct result of stable cluster formation, efficient data aggregation, and reduced retransmissions.

8.6. End-to-end delay analysis

The average end-to-end delay recorded for the protocols is: 145 ms for LEACH, 130 ms for HEED, 220 ms for PEGASIS, and 110 ms for AI-EERP. AI-EERP achieves: 24% lower delay than LEACH, 15% lower delay than HEED, 50% lower delay than PEGASIS. PEGASIS suffers from high latency due to its chain-based forwarding structure, while AI-EERP benefits from short, high-quality multi-hop routes selected using AI-driven metrics, making it suitable for delay-sensitive IoT applications.

8.7. Additional communication cost for route upkeep

The overhead associated with route maintenance is measured as the share of control packets in total packet transmissions is13.4% for LEACH: 10.1% for HEED, 8.9% for PEGASIS, and 7.2% for AI-EERP. The overhead reduction achieved by AI-EERP is: 46% in contrast to LEACH, 29% in contrast to HEED, and 19% in contrast to PEGASIS.

This clearly demonstrates that AI-based CH prediction significantly reduces unnecessary cluster reformation and control message exchange. Table 4 compares packet delivery ratio and throughput achieved by AI-EERP and the benchmark protocols under identical network conditions.

Table 4. PDR, throughput, delay, and routing overhead for 100 Nodes

Protocol	PDR (%)	Throughput (kbps)	Avg. End-to-End Delay (ms)	Routing Overhead (% of total packets)
LEACH	89.3	18.4	145	13.4
HEED	92.5	19.7	130	10.1
PEGASIS	90.1	17.9	220	8.9
AI-EERP	**97.8**	**23.6**	**110**	**7.2**

The proposed protocol achieves higher packet delivery and throughput, indicating improved routing reliability and reduced packet loss. Stable route selection and avoidance of weak links contribute to consistent data delivery performance. Energy fairness is evaluated using the standard deviation of residual energy among sensor nodes, which reflects how evenly energy consumption is distributed across the network. A lower standard deviation indicates balanced energy usage, while higher values suggest uneven energy depletion and potential formation of energy holes. Table 5 presents a comparative analysis of energy fairness achieved by the proposed protocol and the benchmark routing schemes.

Table 5. Energy fairness comparison (standard deviation of residual energy)

Protocol	σ_e at Round 1000 (J)
LEACH	0.52
HEED	0.41
PEGASIS	0.44
AI-EERP	**0.28**

Lower σ_e means more balanced energy consumption. AI-EERP should clearly look best here. As shown in Table 5, the proposed AI-EERP achieves the lowest standard deviation of residual energy among all evaluated protocols, indicating a more balanced distribution of energy consumption across sensor nodes. In contrast, conventional protocols exhibit higher energy variation due to uneven load distribution and frequent selection of the same nodes for routing roles. The improved energy fairness of AI-EERP can be attributed to its prediction-based routing and adaptive cluster-head selection, which prevent excessive energy depletion of individual nodes and contribute to sustained network stability. Network lifetime is further analyzed by examining the round at which the last sensor node exhausts its energy under different network sizes. The LND metric reflects the maximum operational duration of the network and provides insight into protocol scalability. Table 6 presents the LND values observed for varying numbers of sensor nodes using the proposed and benchmark routing protocols.

Table 6. LND vs number of nodes

Nodes (N)	Protocol	LND (Round)
50	LEACH	950
	HEED	1050
	PEGASIS	1120
	AI-EERP	**1400**
100	LEACH	1100
	HEED	1200
	PEGASIS	1250
	AI-EERP	**1600**
200	LEACH	870
	HEED	950
	PEGASIS	1000
	AI-EERP	**1300**

As shown in Table 6, the proposed AI-EERP consistently achieves a higher LND across all network sizes, indicating a longer overall network lifetime compared to conventional protocols. The improvement becomes more pronounced as the number of sensor nodes increases, demonstrating the protocol's ability to scale effectively in denser deployments. This enhanced longevity results from balanced energy consumption and adaptive routing decisions that prevent early exhaustion of individual nodes. This table supports a scalability discussion: even under higher density (N=200), AI-EERP maintains superior lifetime. The packet delivery performance shown in Figure 3 indicates that AI-EERP consistently achieves a higher packet delivery ratio across all evaluated scenarios. This improvement reflects more reliable routing decisions and stable communication paths. By avoiding low-energy or unreliable links, the proposed protocol reduces packet loss and ensures dependable data delivery to the base station. As shown in Figure 3, AI-EERP achieves the highest packet delivery ratio among all evaluated protocols. The improved performance is attributed to stable routing paths and reduced packet loss, which enhance the reliability of data transmission to the base station.

Figure 4 illustrates the throughput achieved by LEACH, HEED, PEGASIS, and the proposed AI-EERP under identical network conditions. It can be observed that AI-EERP consistently delivers higher throughput than the benchmark protocols throughout the simulation. This improvement indicates more effective utilization of available communication resources and sustained data transmission to the base station.

As shown in Figure 4, the throughput comparison of the evaluated routing protocols. It can be observed that AI-EERP achieves the highest throughput among all methods. The improved performance is due to stable routing paths and reduced packet loss, which enable efficient data transmission to the base station.

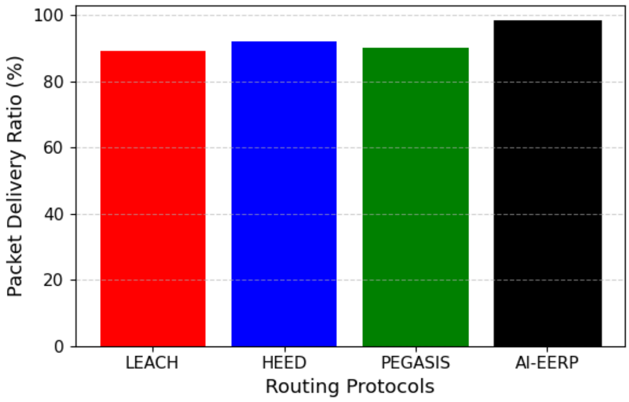

Figure 3. Packet delivery ratio comparison among LEACH, HEED, PEGASIS, and the proposed AI-EERP protocol

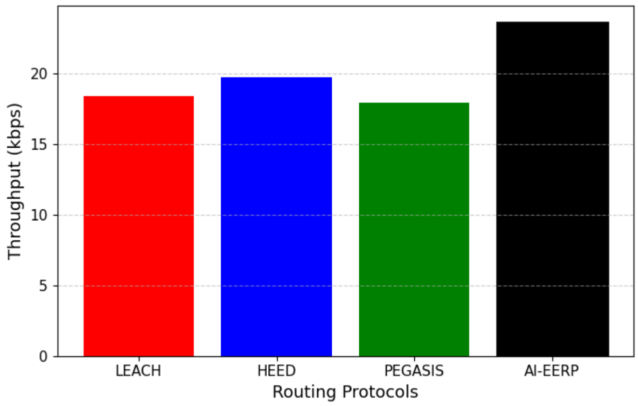

Figure 4. Throughput performance comparison of LEACH, HEED, PEGASIS, and the proposed AI-EERP protocol

8.8. Summary of findings

The experimental results demonstrate that AI-EERP outperforms conventional energy-efficient protocols across all key metrics. The results across all evaluation metrics indicate a consistent performance advantage of the proposed AI-EERP protocol over conventional routing schemes. The improvements are evident in terms of extended network lifetime, higher data delivery reliability, reduced delay, and balanced energy utilization. These findings demonstrate the effectiveness of integrating predictive intelligence into routing decisions.

Table 7 provides a qualitative comparison of the proposed AI-EERP protocol with conventional routing protocols across multiple performance metrics. The comparison highlights the relative strengths of each protocol in terms of energy efficiency, reliability, and network performance.

Table 7. Performance comparison of AI-EERP With conventional energy-efficient routing protocols

Metric	LEACH	HEED	PEGASIS	AI-EERP (Proposed)
Network Lifetime	Medium	Medium–High	High	Highest
Residual Energy	Low	Medium	Medium	High
PDR	Medium	High	Medium	Highest
Throughput	Medium	Medium	Low– Medium	High
Delay	Medium	Medium –Low	High	Lowest
Routing Overhead	High	Medium	Low	Low
Energy Fairness	Low	Medium		High

As shown in Table 7, AI-EERP demonstrates superior performance in key metrics such as network lifetime, packet delivery ratio, throughput, and energy fairness, while maintaining lower delay and routing overhead. This confirms the effectiveness of the proposed approach in achieving balanced and efficient network operation.

9. CONCLUSION AND FUTURE WORK

This study introduces an AI-EERP for future WSNs. The proposed protocol combines machine learning–based residual energy estimation, link-quality assessment, flexible cluster-head selection combined with efficient multi-hop routing to overcome the shortcomings of conventional energy-efficient routing schemes such as LEACH, HEED, and PEGASIS. By integrating predictive analysis with hierarchical routing mechanisms, AI-EERP enhances cluster stability, minimizes communication overhead, and promotes balanced energy utilization across the network.

Extensive NS-3 simulations demonstrated that AI-EERP significantly outperforms benchmark protocols in terms of: i) total operational period (longer FND, HND, and LND periods), ii) residual energy preservation, iii) PDR and throughput, iv) reduced end-to-end delay, v) lower route cost associated with route maintenance, and vi) higher energy fairness and stability.

The findings confirm that AI-driven decision-making significantly improves routing adaptability and long-term sustainability in energy-constrained WSN environments. Owing to these characteristics, AI-EERP is particularly suitable for contemporary IoT applications such as encompassing smart cities, industrial automation, precision farming, and environmental assessment, where reliable communication and prolonged autonomous operation are critical requirements. Although AI-EERP demonstrates strong performance, several research opportunities remain for future exploration:

a. On-node lightweight learning models: Future implementations can incorporate highly optimized ML models such as TinyML, quantized neural networks, or decision-tree compression to enable faster and energy-efficient inference directly on sensor nodes.
b. Federated and distributed learning: Integrating federated learning can allow nodes to collaboratively update models without transmitting raw data, thereby enhancing scalability and data privacy while reducing BS communication overhead.
c. Real-time adaptation under mobility: Although AI-EERP supports semi-static environments, extending the protocol to handle rapid node mobility, UAV-assisted sensing, and dynamic topologies remains a promising area.
d. Hardware testbed deployment: Future work should involve implementing AI-EERP on physical hardware platforms such as Raspberry Pi, ESP32, or ARM-based sensor nodes to evaluate real-world constraints like CPU load, energy drain, and environmental noise.
e. Security-enhanced predictive routing: Machine learning introduces new attack surfaces. Enhancing AI-EERP with secure routing features—anomaly detection, trust scoring, or adversarial ML resistance—can strengthen its resilience.
f. Cross-layer optimization: Extending the AI-driven decision-making to include MAC-layer scheduling, duty cycling, and application-level QoS policies may further improve energy efficiency and performance.
g. Multi-objective optimization: Future versions of AI-EERP may incorporate multi-objective learning models that jointly optimize energy, delay, reliability, and fairness, enabling more adaptive trade-offs based on real-time requirements.

AI-EERP demonstrates that the integration of artificial intelligence into routing protocol design marks a transformative step for next-generation WSNs. With further research into lightweight models, distributed learning, real-world deployment, and secure AI-driven networking, AI-EERP can evolve into a highly adaptable, scalable, and intelligent routing framework for the IoT ecosystem.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Shamsher Singh	✓	✓		✓					✓	✓		✓		
Mandeep Kumar		✓	✓	✓	✓	✓	✓	✓	✓	✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author states that there are no financial interests or personal relationships that could reasonably be perceived as influencing the work reported in this study.

INFORMED CONSENT

No human participants or identifiable personal data were involved in this study; informed consent was not required.

ETHICAL APPROVAL

As this study did not involve human participants or animal experimentation, the requirement for ethical approval did not apply.

DATA AVAILABILITY

The data corroborating the findings of this study can be derived from the contact author upon justified request.

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BIOGRAPHIES OF AUTHORS

Shamsher Singh is a faculty member in the Department of Computer Science at AB College. He has been actively involved in teaching and research since 2002, with more than two decades of academic experience. His primary area of specialization is data mining, with a strong focus on both theoretical foundations and practical applications. Dr. Singh has taught and conducted research in several core domains, including data preprocessing, pattern recognition, predictive modeling, and machine learning. His research interests extend to knowledge discovery from large datasets, intelligent data analysis, and the application of machine learning techniques to real-world problems. He has published research articles in peer-reviewed journals and conference. Dr. Singh continues to contribute to curriculum development and academic research, with ongoing work aimed at improving data-driven decision-making systems. He can be contacted via email at: drsamsingh1612@gmail.com.

Mandeep Kumar received the B.Tech. degree in computer science and engineering from Dr. B. R. Ambedkar National Institute of Technology, Jalandhar, Punjab, India, in 2003, and the M.Tech. degree in computer science and engineering from Dr. B. R. Ambedkar National Institute of Technology, Jalandhar, Punjab, India, in 2013. He completed the Ph.D. degree from I. K. Gujral Punjab Technical University (IKGPTU), Kapurthala, Punjab, India. He is currently working as an academic and researcher in the field of computer science. His research interests include wireless sensor networks, network security, energy-efficient routing protocols, and intelligent data analysis techniques. He has been actively involved in teaching undergraduate and postgraduate courses and has published research articles in peer-reviewed journals and conference proceedings. His current research focuses on secure and energy-aware communication models for resource-constrained networks. He can be contacted via email at: mandeep.recj@gmail.com.