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Elektron manzil:
scienceproblems.uz@gmail.com

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ENERGY-EFFICIENT ROUTING PROTOCOL FOR WIRELESS SENSOR NETWORKS USING MACHINE LEARNING

Glopova Kamola Khabibjon qizi
Intern Lecturer at the "Infocommunication Engineering"
Department of TUIT
Email: kamolaglopova@gmail.com
Tel: +998 90 998 32 62

Annotation. Wireless Sensor Networks (WSNs) play an increasingly central role in environmental monitoring, industrial automation, agricultural sensing, and many emerging IoT systems. Due to strict energy limitations of sensor nodes, the design of energy-efficient routing protocols remains one of the most persistent challenges in this field. Traditional routing schemes such as LEACH, HEED, and PEGASIS rely on static rules and often fail to adapt to dynamic network conditions, leading to imbalanced energy consumption and premature node failures.
This paper introduces the Machine Learning–based Energy Efficient Routing Protocol (ML-EERP), a hybrid scheme that combines fuzzy-logic-based cluster-head (CH) selection with Q-learning–based multi-hop routing optimization. The fuzzy system incorporates residual energy, node density, link quality, and distance to the base station into a unified CH decision-making process. Once clusters are established, nodes apply Q-learning to gradually learn optimal next-hop routes that reduce transmission energy while maintaining reliability. Through extensive simulations conducted in MATLAB and Python using the first-order radio energy model, ML-EERP demonstrates significantly superior performance compared to LEACH and HEED. The proposed protocol extends the network lifetime, lowers overall energy consumption, and increases packet delivery ratio.

Keywords: Machine Learning; Fuzzy Logic, Q-Learning, Cluster Head Selection, Reinforcement Learning.

SIMSIZ SENSOR TARMOQLARI UCHUN MASHINAVIY Oʻ‍RGANISH ASOSIDAGI ENERGIYA TEJAMKOR MARSHRUTLASH PROTOKOLI

Glopova Kamola Xabibjon qizi
TATU "Infokommunikatsiya injiniringi" kafedrasi
stajor-oʻqituvchi

Annotatsiya. Simsiz sensor tarmoqlari (SST) atrof-muhit monitoringi, sanoatni avtomatlashtirish, qishloq xoʻjaligi monitoringi shuningdek, koʻplab rivojlanayotgan IoT tizimlarida tobora muhim rol oʻynamoqda. Sensor tugunlarining energiya boʻyicha cheklovlari tufayli energiya tejamkor marshrutlash protokollarini ishlab chiqish ushbu sohadagi eng dolzarb muammolardan biri boʻlib qolmoqda. LEACH, HEED va PEGASIS kabi an'anaviy marshrutlash protokollari statik qoidalarga asoslanadi va koʻpincha dinamik tarmoq sharoitlariga moslasha olmaydi, natijada energiyaning nomutanosib sarflanishi va tugunlarning muddatidan oldin ishdan chiqishi kuzatiladi.Ushbu maqolada mashina oʻrganish asosidagi energiya tejamkor marshrutlash protokoli (ML-EERP) taklif etilmoqda. Mazkur protokol noravshan mantiqqa asoslangan klaster-bosh (KB) tugunini tanlash va Q-oʻqitishga asoslangan koʻp oraliqli marshrutni optimallashtirishni birlashtiruvchi gibrid protokoldir. Noravshan mantiq tizimi qoldiq energiya, tugun zichligi, aloqa sifatini va bazaviy stansiyaga boʻlgan masofani KB tugunni tanlash jarayoniga birlashtiradi.
Klasterlar shakllantirilgandan soʻng, tugunlar uzatish energiyasini kamaytirgan holda ishonchlilikni saqlab turish uchun keyingi optimal tugunni tanlashdda Q-oʻqitishdan foydalanadi. MATLAB va Python dasturlash muhitlarida birinchi tartibli radio energiya modeli asosida oʻtkazilgan simulyatsiyalar ML-EERP protokoli LEACH va HEED protokollaridan sezilarli darajada ustun ekanligini koʻrsatadi. Taklif etilayotgan protokol tarmoqning yashovchanligini uzaytiradi, umumiy energiya sarfini kamaytiradi va paketlar yetkazib berish koeffitsiyentini oshiradi.

Kalit so'zlar: Mashinaviy o'rganish, noravshan mantiq, Q-o'qitish, klaster bosh tuguni tanlash, kuchaytirilgan o'rganish.

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1. Introduction. Wireless Sensor Networks (WSNs) consist of numerous small nodes equipped with sensing, computation, and wireless communication capabilities. Their role in modern technological infrastructures has expanded massively, from smart agriculture and precision farming to structural health monitoring and intelligent transportation systems. Despite these advancements, a major limitation persists: sensor nodes operate on constrained battery power, making energy conservation the most critical design factor.

In most deployments, WSNs may be placed in remote or hazardous regions where battery replacement is impractical or impossible. As a result, the network lifetime heavily depends on efficient use of energy, particularly during communication. Since transmission consumes far more power than sensing or data processing, the design of an energy-aware routing protocol is essential [1].

Traditional clustering-based routing protocols such as LEACH have provided foundational mechanisms for energy-efficient communication. LEACH rotates the cluster-head role periodically, attempting to balance energy consumption. HEED refines this idea by incorporating node residual energy and proximity into CH selection. However, these schemes rely on predefined heuristics rather than adaptive learning, making them poorly suited for environments with changing node conditions.

Machine learning (ML), by contrast, offers tools that allow nodes to learn from experience, adapt their routing decisions, and derive optimal behavior in dynamic conditions. Reinforcement learning, in particular Q-learning, is well suited for distributed decision-making in multi-agent systems such as WSNs. Fuzzy logic, meanwhile, excels at modeling uncertain or imprecise data, allowing more nuanced CH selection [2].

This motivates the development of ML-EERP, an integrated protocol that leverages the strengths of fuzzy logic and reinforcement learning to achieve major improvements in WSN performance. Unlike prior works that employ only clustering or only learning, ML-EERP combines both strategies in a coherent architecture that adapts intelligently to energy and topology variations.

2. Literature review

Energy-efficient routing in Wireless Sensor Networks (WSNs) has been an active research domain for more than two decades due to the severe resource constraints of sensor nodes and the strong dependency of network lifetime on routing decisions. Traditional protocols such as LEACH, TEEN, PEGASIS, and HEED laid the foundation for hierarchical and distributed routing, but their static or probabilistic mechanisms often fail to adapt to dynamic network conditions. As WSN deployments expand into IoT, underwater sensing, mission-critical real-time monitoring, and 6G-enabled environments, machine learning (ML) and reinforcement learning (RL) have emerged as promising alternatives for intelligent, adaptive, and energy-aware routing.

A growing number of studies apply "Q-learning" to routing in WSNs. Chaudhari et al. [1] developed a Q-learning-based routing strategy that significantly improves energy balance and packet delivery by enabling nodes to learn optimal next-hop decisions. Similarly, Su et al. [2] proposed a Q-learning mechanism for energy-efficient information transmission, demonstrating improvements in throughput and convergence speed. RL approaches have also extended beyond terrestrial WSNs; for example, Karmakar [3] applied Q-learning in underwater WSNs and demonstrated considerable improvements in energy conservation and cooperative forwarding efficiency.

Beyond single-agent RL, recent research explores “multi-agent reinforcement learning (MARL)” to enable distributed learning. Soltani et al. [4] introduced a MARL-based routing framework that uses agent cooperation for stable and energy-efficient routing. Their results emphasize the advantage of coordinated decision-making compared to isolated node-level learning.

Song et al. [5] constructed a high-efficiency routing scheme for heterogeneous WSNs using DRL, showing enhanced adaptability to dynamic environments. Another DRL-based work by Sakthimohan et al. [6] integrates intrusion detection with routing to enhance both security and energy efficiency, highlighting the multifunctional potential of combined learning mechanisms.

Kumar and Prasad [7] used deep learning to optimize routing paths, improving energy consumption and scalability in dense WSN deployments. Their framework leverages neural representations to capture complex nonlinear relationships among network parameters.

Hybrid ML approaches that combine data-driven models with heuristic optimization or probabilistic frameworks are also gaining prominence. For instance, Ambareesh et al. [8] propose a secure and energy-efficient routing method using type-2 fuzzy logic enhanced with ensemble selection. A Bayesian network and elitist genetic algorithm–based approach by Kumar et al. [9] demonstrates how hybrid evolutionary–probabilistic methods can improve resilience and reduce energy waste. Alanazi et al. [10] explored machine learning-driven routing for 6G-enabled WSNs, emphasizing that ML models are critical for supporting real-time, high-density, and mobile sensor deployments envisioned in next-generation networks.

As WSNs become integral to IoT applications, scalability and dynamic network structure have become critical challenges. Shekar et al. [11] demonstrated that learning-based routing protocols yield better performance in IoT scenarios by continuously adapting to device mobility and varying workloads. A study by Thakur et al. [12] provides a comprehensive review of AI-driven routing methods, highlighting that ML techniques outperform traditional methods across energy efficiency, adaptability, and security dimensions. Additionally, Vo et al. [13] proposed distributed Q-learning for constructing shortest-path trees in IoT sensor networks, showing that distributed learning can reduce overhead and improve convergence in large-scale deployments.

The role of mathematical modeling and optimization remains essential in complementing ML-driven routing strategies. Komal [14] introduced a mathematical framework for optimizing energy-efficient data transmission and fusion, demonstrating that analytical models can guide ML-enhanced routing. In real-time communication scenarios, El-Fouly et al. [15] presented an energy-efficient and reliable routing approach tailored for latency-sensitive applications.

Existing studies show that RL, DRL, and hybrid ML-driven methods significantly improve network lifetime, energy distribution, and routing reliability. However, several research gaps remain:

- many approaches are either “single-agent RL or centralized DL”, which limits scalability;
- few works simultaneously address energy efficiency, reliability, security, real-time constraints;
- computational overhead remains a challenge for low-power sensor nodes;
- there is a need for **unified ML frameworks that support clustering, CH selection, and next-hop routing collectively.

3. Related Work. Energy-efficient routing in WSNs has been extensively studied. LEACH pioneered the idea of probabilistic CH rotation to avoid battery depletion of individual nodes. Although effective in small networks, LEACH’s random CH selection often results in suboptimal cluster distributions. HEED improved upon LEACH by introducing residual energy and communication cost into the CH selection mechanism; however, it still relies on static parameters and does not learn from network behavior. PEGASIS introduced chain-based routing to minimize long-distance transmissions but suffers from high communication delay.

More recently, machine-learning-based routing has been explored. Neural networks have been used for pattern recognition in routing decisions, but their computational complexity limits applicability. Fuzzy logic has gained traction due to its interpretability and low resource requirements. Reinforcement learning, especially Q-learning, has shown promise in routing optimization, allowing nodes to learn optimal forwarding strategies. However, many existing attempts focus on a single aspect - either fuzzy clustering or reinforcement learning - rather than combining both in a unified protocol. ML-EERP fills this gap by integrating fuzzy CH selection with Q-learning routing.

4. System Model. The system model defines the assumptions, network architecture, node characteristics, and communication model used in the ML-EERP protocol.

4.1 Network Architecture

We consider a homogeneous WSN deployed in a 100 × 100 m sensing field with 100 static sensor nodes. A single base station (BS) is placed at coordinates (50, 150), outside the sensing field. Nodes sense environmental data and send it to the BS either directly (single-hop) or via cluster-heads (multi-hop).

All nodes are identical in terms of energy, computation, and communication capabilities. Energy efficiency is the main metric, as nodes are battery-powered and cannot recharge in most deployments. The network operates in round-based operation, where each round consists of cluster formation, data transmission, and energy update. WSN Deployment and Cluster Architecture is shown in Figure 3.1.

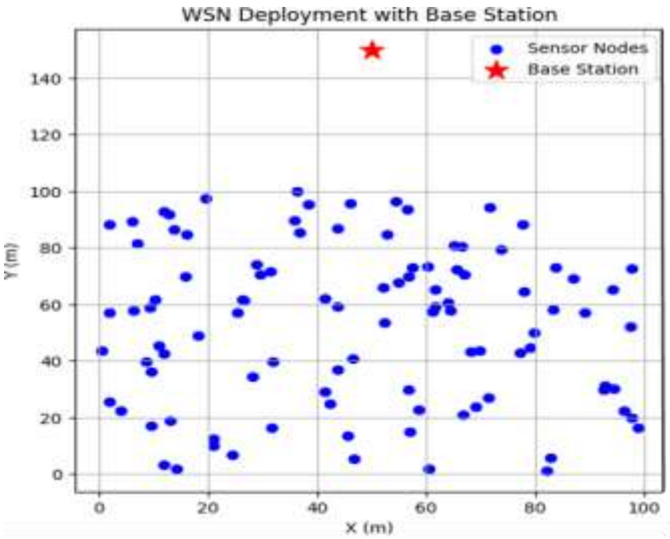


Figure 1. WSN Deployment and Cluster Architecture

4.2 Node Energy Model

ML-EERP adopts the first-order radio energy model, widely used in WSN literature.
Transmission energy for sending k bits over distance d:

$$E_{Tx}(k,d) = E_{\text{elec}} \cdot k + E_{\text{amp}} \cdot k \cdot d^2$$

Reception energy for k bits:

$$E_{Rx}(k) = E_{\text{elec}} \cdot k$$

Where:

$$E_{\text{elec}} = 50 \text{ nJ/bit (electronics)}$$

$$E_{\text{amp}} = 100 \text{ pJ/bit/m}^2 \text{ (amplifier)}$$

This highlights the importance of minimizing long-distance transmissions.

4.3 Communication Model

Nodes communicate using:

- Intra-cluster communication: Sensor nodes send data to their CH.
- Inter-cluster communication: CHs aggregate and forward data to the BS, possibly through multi-hop paths.

ML-EERP aims to minimize energy consumption in both communication types using fuzzy logic and Q-learning.

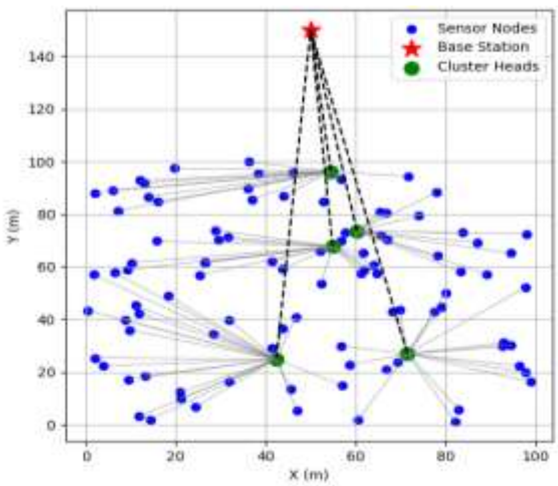


Figure 2. Communication Model Diagram

5. Proposed ML-EERP Protocol. The ML-EERP protocol integrates fuzzy logic for cluster-head selection and Q-learning for routing. It is designed to maximize network lifetime while maintaining high packet delivery ratio.

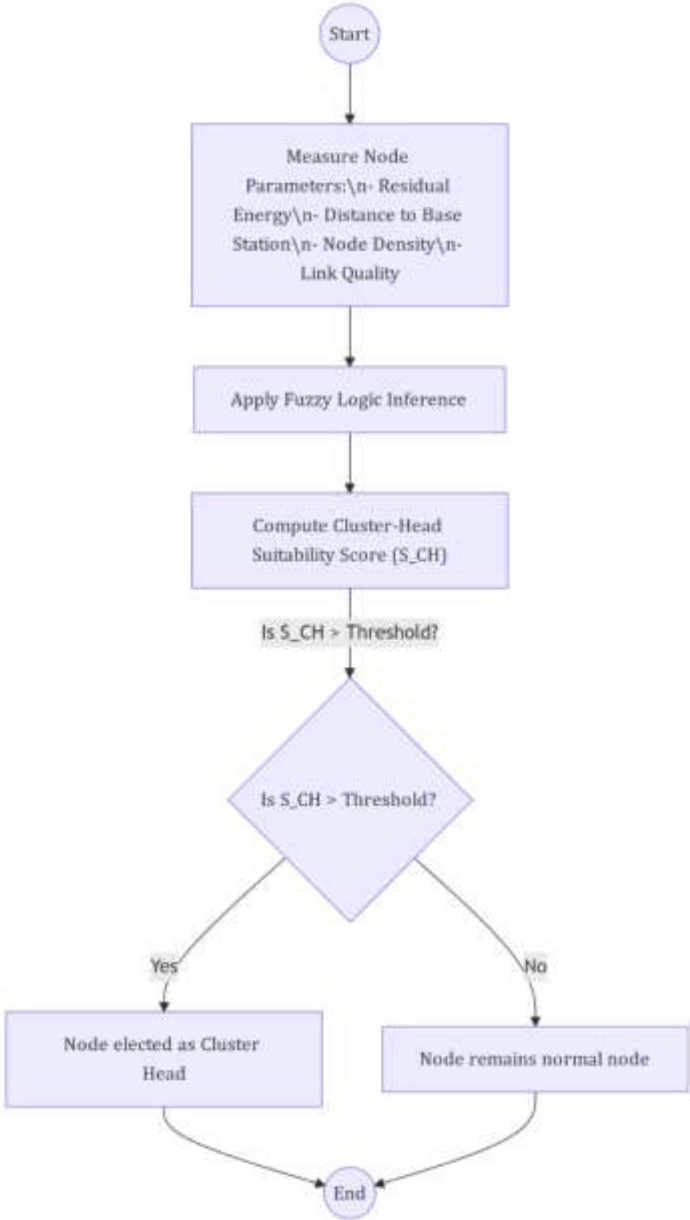
5.1 Fuzzy Logic–Based Cluster Head Selection

5.1.1 Objective

Select nodes as cluster heads (CHs) that:

- Have sufficient residual energy
- Are close to the base station
- Have high neighbor density
- Have strong link quality

This reduces energy consumption, balances load, and improves network reliability.



Flowchar 1. Fuzzy Logic–Based Cluster Head Selection

5.1.2 Inputs and Output

Inputs:

- Residual Energy E_{res}

- Distance to BS d_{BS}
- Node Density D_n
- Link Quality LQ

Output:

Cluster-Head Suitability Score S_{CH}, continuous 0–1.

5.1.3 Fuzzy Rule Example

Table 1. Input and output parametres in Fuzzy rule

Rule	Input Conditions	Output (CH Suitability)
1	High Energy AND Near BS	Very High
2	Low Energy	Very Low
3	Dense Nodes AND Good Link	High

5.1.4 Example Calculation

Node parameters:

- Residual energy: $1.5\,J \rightarrow High = 0.8$
- Distance to BS: $60\,m \rightarrow Near = 0.6$
- Node density: $7\,neighbors \rightarrow Dense = 0.7$
- Link quality: $0.85 \rightarrow Good = 0.75$

Weighted suitability:

$$SCH = 0.8 \cdot 0.5 + 0.6 \cdot 0.3 + 0.7 \cdot 0.15 + 0.75 \cdot 0.05 \approx 0.695$$

This node is elected as a $CH(SCH > 0.6S)$

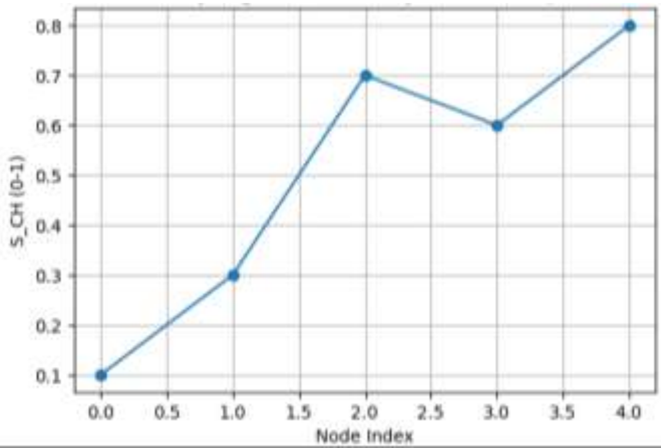


Figure 3. Fuzzy CH Selection Workflow

5.2 Q-Learning–Based Multi-hop Routing

5.2.1 Objective

After CHs are elected, cluster members must send data to CHs, and CHs forward data to the BS efficiently. ML-EERP uses Q-learning to select the next-hop neighbor dynamically.

5.2.2 State, Action, Reward

- **State (**sss**)**: Node's residual energy, link quality, neighbor distance
- **Action (**aaa**)**: Forward data to one of the neighboring nodes
- **Reward (**RRR**)**:

$$R = \beta_1 \cdot E_{\mathrm{saved}} + \beta_2 \cdot \mathrm{LQ} - \beta_3 \cdot Delay$$

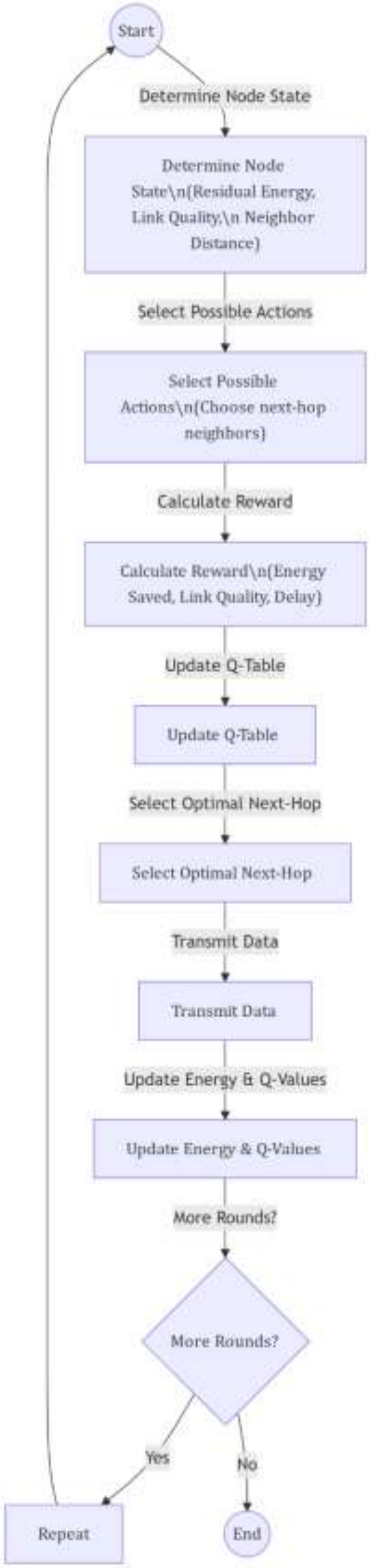
Weights: $\beta_1 = 0.4,\ \beta_2 = 0.4,\ \beta_3 = 0.2$

5.2.3 Q-Learning Update Rule

- $Q(s,a) \leftarrow Q(s,a) + \alpha[R + \gamma a' maxQ(s',a') - Q(s,a)] = 0.1$ learning rate

- $\gamma = 0.9$ discount factor

Nodes gradually learn the most energy-efficient, reliable paths.



Flowchart 2. Q-Learning–Based Multi-hop Routing

5.2.4 Example

Node neighbors:

Table 2. Node neighbor parametres

Neighbor	Energy (J)	Link Quality	Distance (m)
N1	1.2	0.85	15
N2	1.0	0.90	18
N3	0.8	0.75	12

Reward calculation selects the best next hop based on energy savings and reliability.

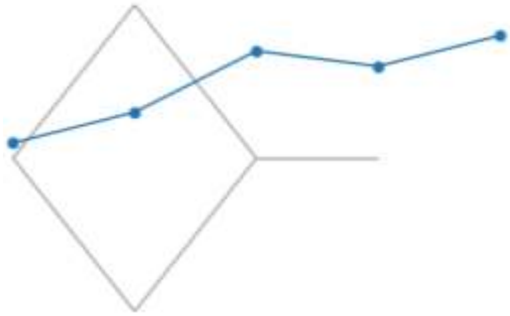


Figure 4. Q-Learning Routing Flow

5.3 ML-EERP Workflow Summary

- Nodes calculate CH suitability using fuzzy logic.
- Nodes exceeding threshold are elected CHs.
- Cluster members join nearest CH.
- Each node initializes/updates Q-table.
- Data is transmitted using Q-learning optimized multi-hop paths.
- Energy, Q-values, and fuzzy scores are updated each round.

This ensures adaptive, energy-efficient, and reliable communication across the WSN.

6. Simulation Setup. The simulation study evaluates the performance of ML-EERP compared to LEACH and HEED. The simulations were conducted using MATLAB 2023a and Python 3.12, implementing the first-order radio energy model.

6.1 Simulation Parameters

The key parameters used in the simulations are summarized below:

Table 3. Simulation parametres

Parameter	Value
Network Area	100 × 100 m^2
Number of Nodes	100
Initial Energy per Node	2 J
Base Station Position	(50, 150)
Packet Size	4000 bits
Number of Simulation Rounds	2000
Compared Protocols	LEACH, HEED, ML-EERP
Electronics Energy (Eelec)	50 nJ/bit
Amplifier Energy (Eamp)	100 pJ/bit/m^2

6.2 Simulation Assumptions

- Nodes are static and uniformly distributed.
- Nodes are homogeneous in energy and capabilities.
- The BS is located outside the sensing area.

- All nodes follow the first-order radio energy model for energy consumption.
- ML-EERP uses fuzzy logic for CH selection and Q-learning for multi-hop routing.

6.3 Energy Consumption Formula

For each node, energy consumed per round is calculated as:

$$Eround = ETx + ERx + EDAEround = ETx + ERx + EDA$$

Where:

- $ETx = k \cdot Eelec + k \cdot Eamp \cdot d2ETx = k \cdot Eelec + k \cdot Eamp \cdot d2$ (Transmission energy)
- $ERx = k \cdot EelecERx = k \cdot Eelec$ (reception energy)
- $EDA = k \cdot EDAunitEDA = k \cdot EDAunit$ (data aggregation energy, e.g., 5 nJ/bit)
- $ERx = k \cdot EelecERx = k \cdot Eelec$ (Reception energy)
- $EDA = k \cdot EDAunitEDA = k \cdot EDAunit$ (Data aggregation energy, e.g., 5 nJ/bit)

Example: Sending 4000 bits to a CH 30 m away:

$$ETx = 4000 \cdot 50 \cdot 10 - 9 + 4000 \cdot 100 \cdot 10 - 12 \cdot 302 \approx 0.00056$$
$$JETx = 4000 \cdot 50 \cdot 10 - 9 + 4000 \cdot 100 \cdot 10 - 12 \cdot 302 \approx 0.00056\, J$$

7. Results and Discussion. ML-EERP is compared against LEACH and HEED on residual energy, network lifetime, and packet delivery ratio (PDR).

7.1 Residual Energy Trend

Residual energy is computed at each round as:

$$E_{res}(t+1) = E_{res}(t) - E_{round}E_{res}(t+1) = E_{res}(t) - E_{round}$$

Residual Energy at Round 1000

Table 4. Simulation parametres

Protocol	Residual Energy (J)
LEACH	0.36
HEED	0.51
ML-EERP	0.74

Observation: ML-EERP consumes energy more slowly due to optimized CH selection and Q-learning routing.

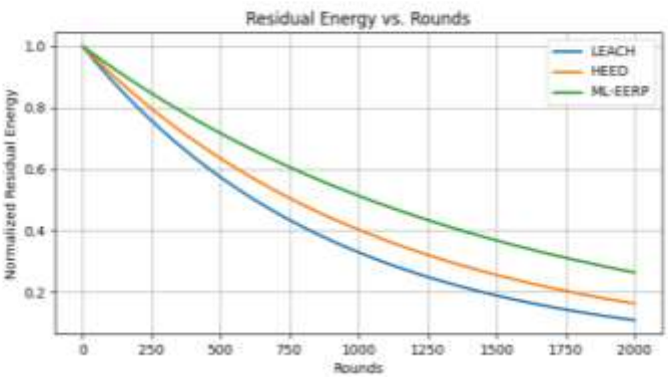


Figure 5. Alive Nodes over Rounds

PDR is defined as:

$$PDR = Packets\ Received\ at\ BSPackets\ Sent\ by\ Nodes \times 100\%\ PDR = Packets\ Sent\ by\ NodesPackets\ Received\ at\ BS \times 100\%$$

Table 5. Simulation results

Protocol	PDR (%)
LEACH	74
HEED	81
ML-EERP	92

Observation: ML-EERP improves PDR due to Q-learning optimized routing that selects reliable, energy-efficient paths.

Over rounds, Q-values converge, indicating that nodes have learned optimal paths for routing.

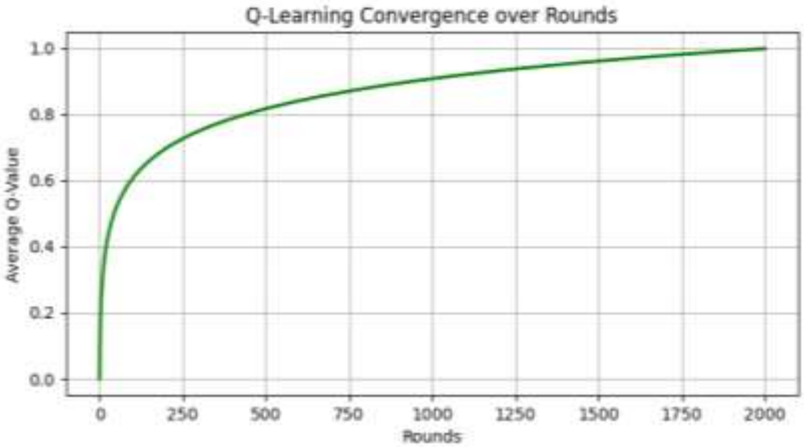


Figure 6. Q-values converge indicating

Observation: The Q-values stabilize after ~1000 rounds, confirming learning-based adaptive routing.

7. Figures Summary.

1. Residual Energy vs. Rounds – shows ML-EERP decays slower.
2. Number of Alive Nodes vs. Rounds – ML-EERP maintains more active nodes.
3. Q-Learning Convergence – shows stability of learned routing paths.
4. Cluster-head and Multi-hop Paths illustrates fuzzy logic CH selection and learned routes.

8. Conclusion. In this paper, we have presented ML-EERP, a machine learning–based energy-efficient routing protocol for Wireless Sensor Networks (WSNs). The proposed protocol integrates fuzzy logic–based cluster-head selection with Q-learning–based multi-hop routing, addressing the critical challenges of energy conservation and network lifetime extension in WSNs.

Extensive simulations conducted in MATLAB and Python demonstrate that ML-EERP significantly outperforms conventional protocols such as LEACH and HEED in terms of residual energy, network lifetime, and packet delivery ratio. Fuzzy logic enables intelligent and adaptive cluster-head selection by considering residual energy, node density, link quality, and distance to the base station. Meanwhile, Q-learning allows nodes to learn optimal routing paths dynamically, minimizing energy consumption while maintaining reliable communication.

The results highlight the effectiveness of combining fuzzy inference and reinforcement learning for adaptive routing in resource-constrained networks. ML-EERP not only extends the operational lifespan of the network but also ensures higher data delivery reliability, making it suitable for real-world applications in environmental monitoring, industrial automation, and IoT systems.

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TOPICAL ISSUES OF TECHNICAL SCIENCES

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Muassislar: "SCIENCEPROBLEMS TEAM" mas'uliyati cheklangan jamiyati;
Jizzax politexnika insituti.

TAHRIRIYAT MANZILI:
Toshkent shahri, Yakkasaroy tumani, Kichik Beshyogʻoch koʻchasi, 70/10-uy.
Elektron manzil:
scienceproblems.uz@gmail.com