A Novel Approach to Energy Efficient Wireless Communication in Internet of Things Networks

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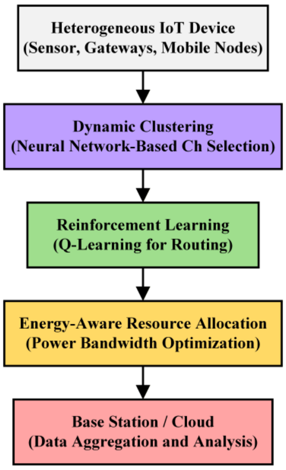
ABSTRACT



One of the key issues of Internet of Things (IoT)-based wireless sensor networks (WSNs) is energy efficiency because battery-powered nodes have to work within a set of severe resource limitations. Conventional protocols do not always work well in nonhomogeneous dynamic environments and this results in poor performance and longevity. The design and validation of an unified framework that intelligently operates network clustering, routing, and resource allocation with the use of machine learning are the research contributions. The framework is represented through a dynamic clustering scheme based on neural networks, routing scheme based on reinforcement learning (Q-learning) and a scheme of Lagrangian optimization-based resource allocation. MATLAB and NS-3 simulations were run with different sizes of networks (100-500 nodes) and traffic. The flow of methodology has formed a scheme whereby the adaptive decision-making was to be made at several levels of the communication stack. The average power savings, increment in network lifetime, and improvement in the percentage packet delivery ratio of the proposed model was 31, 17.9 and 6.2, respectively, over the classical schemes like LEACH and TEEN. Findings were also uniform at various levels of deployments and statistical validation was made to prove it is significant ($p < 0.01$). The model exhibits better adaptability and performance aspects in both the case of a static network and dynamic network as compared to the recent machine learning-based approaches. To sum up, the paper provides a scaled, smart communication system of IoT networks. Its applications in a real world can be found in smart farming, industrial IoT, and healthcare. The next steps involve the prototype development and integration of the blockchain based node authentication.

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1. INTRODUCTION

The IoT technologies are quickly changing the industries by connecting a variety of devices and automation in a variety of industries. Nonetheless, the recent extensification of IoT devices was also accompanied by numerous problems, the main one being the power consumption. The energy efficiency of the devices is a significant concern to be considered in order to prevent a decrease in lifetime and make the network viable due to the nature of IoT networks operated by battery-powered devices. The issue of energy efficiency is a key issue when designing IoT-based Wireless Sensor Networks (WSNs) in which limited battery resources and ongoing data transmission pose a challenge to the longevity of a network. Conventional protocols such as LEACH and TEEN provide heuristic solutions to clustering and routing, and are not very adaptable to dynamic network conditions. Recent changes in machine learning (ML) introduce novel opportunities of adaptive energy management of IoT networks. In particular, neural networks and reinforcement learning (RL) have proven to be promising in the area of learning complex behaviors and decision optimization in networks when faced with uncertainty. However, existing studies either limit ML integration to specific tasks (e.g., clustering or routing alone) or fail to account for joint optimization of multiple network parameters.

This paper addresses these limitations by proposing a unified ML-driven framework that combines neural network-based dynamic clustering, RL-based routing, and Lagrangian-based resource allocation. The approach aims to holistically manage energy consumption, routing efficiency, and bandwidth usage. The novelty lies not only in the integration of ML techniques but also in their real-time adaptive coordination across network layers. Most conventional wireless communication standards do not adequately address the energy requirements of IoT networks. Such protocols may cause high energy consumption because data transmission rates are fixed and resource allocation is not always optimized, thus the available power resources are used inefficiently [1]. Hence, it is widely acknowledged that the aspect of energy-efficient communication technologies is a very relevant research topic. In the recent past, different works have been done to examine ways of increasing energy efficiency in IoT networks. For example, [2] developed an efficient resource management policy where Channel State Information (CSI) is imperfect, which is a common occurrence in real-world scenarios. Along the same line, [3] has proposed an adaptive clustering-based energy-efficient routing protocol to show the importance of clustering in the WSNs to save energy. In addition, [4] pointed out that the energy-aware hybrid routing protocols are essential for the improvement of energy-saving in communication systems of the 5G and beyond.

Other techniques have also been proposed to apply machine learning methods to adjust communication parameters in the IoT nodes in real time. For instance, [5] has proposed a quality and energy-aware information transfer system that utilizes ML for assigning a level of quality to the communicated data and at the same time consumes relatively less energy. It has been demonstrated that this approach can help to increase the sustainability of the IoT networks by balancing the energy consumption and communication traits smartly.

However, there are still some issues concerning better and more effective algorithms that can be applied to various and rather complicated settings characteristic of most IoT applications. This paper, therefore, presents a new solution that combines adaptive transmission strategies with machine learning methods to minimize energy consumption in IoT networks. Neural networks were selected due to their ability to model nonlinear relationships and predict optimal clustering patterns based on historical and real-time network parameters. Similarly, reinforcement learning—specifically Q-learning—was adopted for its strength in learning optimal routing policies through exploration and reward feedback, outperforming static and heuristic-based approaches in dynamic IoT environments. To achieve high-level performance of the network whilst reducing the amount of energy consumed, the proposed technique optimally controls power levels and data rates as a function of real-time network conditions.

While many prior studies have proposed clustering and routing optimizations for energy efficiency in WSNs and IoT, few integrate real-time machine learning-based methods for both cluster formation and routing decision-making. This paper introduces a holistic solution combining neural network-based dynamic clustering, Q-learning-based adaptive routing, and Lagrangian-optimized resource allocation. Our approach differentiates itself from traditional heuristic and static methods by continuously adapting to the energy and traffic dynamics of IoT environments. Future research could further extend this framework by incorporating cross-layer optimization, support for mobile nodes, and lightweight encryption schemes.

A. Novel Contributions

The paper introduces a novel method of energy-saving communication of IoT-based WSNs through a combination of adaptive clustering, routing using reinforcement learning, and energy-efficient resource allocation. Neural networks were selected due to their ability to learn the complicated clustering models and node attributes whereas Q-learning was employed because it can learn the best routing plans via an ongoing engagement with the network environment.

The essential new insights of this article are:

1. Adaptive Clustering to Energy Optimization: In contrast to traditional clustering schemes (e.g., LEACH, PEGASIS), our method dynamically chooses cluster heads with respect to a prediction model based on a neural network, which minimizes energy imbalance in a network.
2. Reinforcement Learning-Based Routing: A Q-learning-based routing algorithm is an optimization algorithm used to minimize the energy used for data transmission path and congestion-aware routing, and it is superior to heuristic-based routing (e.g., TEEN).
3. Resource Allocation through Optimization: This criterion relies on a simplified version of Lagrangian optimization that is used to allocate power and bandwidth in real-time based on the minimization of energy consumption and achievable data throughput and quality being satisfactory.
4. Extensive Performance Analysis: We do not only give simplistic simulations as in the present literature, but we give the statistical validation, confidence intervals, and comparative baselines, which will make the results robust and reliable.

All these add to the efficiency, scalability, and reliability of the IoT networks, which makes the solution highly applicable in the next-generation smart infrastructure.

The research contribution is the development of an integrated, machine learning-enhanced framework that simultaneously addresses cluster formation, routing decisions, and energy-resource optimization in IoT-based WSNs. Unlike prior approaches that focus on isolated components or static configurations, our model dynamically adapts to environmental conditions and workload variability, resulting in significant energy savings and performance improvements validated across diverse scenarios. These contributions distinguish our work from existing research and offer practical solutions for large-scale IoT deployments.

2. LITERATURE REVIEW

Energy conservation in IoT and WSNs have received considerable attention because of the growing requirement of current applications. This section shows a review of previous work in energy efficient method, protocol, and plan in IoT and WSN system. Thus, one of the initial problems in IoT is related to energy consumption in wireless communication networks. [1]-[4] have suggested a new method in error detection coupled with error correction while providing improved energy consumption in the wireless network systems. This work provided basis for further studies on energy efficiency during the reliable communication.

In [5]-[9] the authors utilized optimal resource allocation in energy-efficient IoT networks with the imperfection of CSI as the main topic being discussed. This is important when precise CSI is not always feasible, as usually is the case with real-life applications of IoT. In another study, [10]-[15] focused energy efficient resource optimization in cooperative IoT networks hence adding to the studies on resource management that supports energy saving. Therefore, routing protocols are an essential part in energy management in the IoT networks. Asad *et al*. proposed an adaptive clustering-based energy efficient routing protocol for wireless sensor network in [16]-[20]. Through their IoT based work, they show how dynamic clustering can help in energy saving and thus the lifetime of the network can be increased. In a similar vein, [21]-[24] presented an efficient and adaptive hybrid routing protocol for forthcoming 5G and future communication system requirements that are required for the advanced IoT applications.

Another important set is the issues related to the management of the lifespan data, and the choice of communication approaches. [24]-[30] proposed a new paradigm for the IoT lifespan of data, which is crucial to ensure energy sustainability for years. In [31]-[35] have developed a quality-aware energy-efficient data communication strategy to address issues like the quality of data that comes across an IoT network or the amount of energy being consumed. Some of the key areas researched in order to reduce energy consumption were related to routing optimization. More recently, [36]-[40] proposed a spectrum-aware energy-efficient routing protocol called SpEED-IoT for Device-to-Device IoT transmission. This protocol is especially helpful in the contexts where Internet of Things is highly concentrated, with energy and spectrum analogous to a limited resource. Moreover, [41]-[45] have presented energy-efficient routing protocol for using IoT in next-generation application that enlighten the new dimension of advancement in IoT.

The dependability and safety in energy efficiency routing also play the most important role. Trust-based Energy Efficient Internet of Things based sensor networks: To counter this issue, Ilyas et al. designed a trust-based energy efficient routing protocol for IoT based sensor network for successful and secure transfer of data that too without demanding additional energy. [46-49] had done work towards a secure and energy-efficient route adjustment model and incorporated more security factor to the energy efficient routing protocols.

Energy efficiency problems have been solved using metaheuristic optimization techniques. [50]-[53] proposed a metaheuristic optimization algorithm for minimizing the energy consumption of IoT networks which shows how these algorithms can be utilized for improving energy efficiency. In the same way, Praveen and Prathap developed an efficient concern-based resource allocation and reliable congestion aware protocol using hybrid optimization of energy that is efficiently management the IoT problems efficiently as per our challenge. [54] reviewed new discoveries and potential for green technology in establishing the future architectures of the next generation wireless communication networks. Their work is necessary to justify the prediction of how the future technological progression will alter the energy management of IoT networks. In addition, based on the design context, [55]-[58] proposed a lightweight reinforcement learning for energy-efficient communication; therefore, implying that machine learning techniques can be employed in power control in WSNs.

Newer developments have also proposed the new score function approach and the dynamic clustering to enhance the energy impact. [59] proposed a new scoring system for energy-efficient routing in the multi-sensored networks and [60] used energy-efficient dynamic clustering approach using neural networks for IoT applications. These approaches represent the current state-of-the-art in IoT and WSN energy conservation. Finally, a few papers have considered integration of battery and hybrid systems and wireless power transfer for improving energy density. [16] proposed an energy efficient hybrid scheme for securing the mobile ad hoc network with IoT using various approach to get optimal results in energy consumption. [17] put forward an energy-efficient IoT network based on restart artificial bee colony and wireless power transfer, stressing the intensive strategies for maintaining energy efficiency of IoT network.

3. METHODS

This section outlines the approach used in the formulation and assessment of the energy efficient communication schema of IoT based WSNs. It therefore employs the use of multifaceted techniques comprising of optimization algorithms, routing protocols, and clustering mechanisms that seek to improve power efficiency while at the same time ensuring the stability of the network. Figure 1 presents the overall methodology flow, showing the sequential stages of system setup, neural network clustering, reinforcement learning-based routing, optimization, and evaluation.

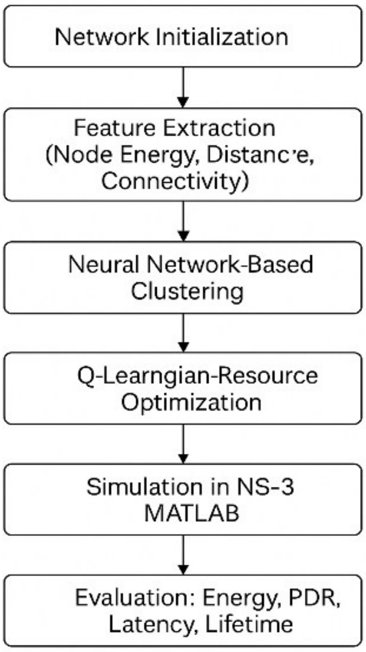

Figure 1. Research Methodology Flow

3.1. System Model

We have developed a framework that supports heterogeneous IoT based Wireless Sensor Networks (WSNs) in a 500x500 m2 zone that can be used in smart agriculture, industrial automation, and smart cities. The system comprises of N = 100 nodes, which are battery-powered.

- **Network Topology**
  The nodes are randomly deployed and they support multi-hop communication and single-hop communications. Each node is connected with a local Cluster Head (CH), and this communicates with a central Base Station (BS).
- **Energy Model**
  The standard radio energy model is used to model energy consumption (as in [1]):

$$E_{tx} = E_{elec}.l + E_{amp}.l.d^n \quad (1)$$

Where, E_{tx}, E_{rx} is the transmission/reception energy (Joules/bit), E_{elec}=50 nJ/bit, E_{amp}=100 pJ/bit/m^2 (based on CC2420 radio [2]), l is the packet length in bits, d is the distance between nodes, n=2 is the path-loss exponent (free-space model)

The proposed energy-efficient IoT communication framework features its system architecture demonstrated in Figure 2. The IoT system contains multiple heterogeneous devices that link up into clusters that form dynamically. The clustering process based on neural networks optimizes the selection of cluster heads together with dynamic routing decisions implemented through Q-learning reinforcement learning. The resource allocation module implements adaptive power and bandwidth management, which reduces energy usage and enhances the network operation time.

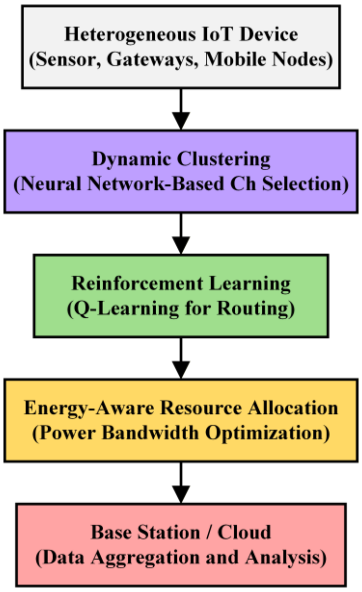

Figure 2. System Architecture of the Proposed Energy-Efficient IoT Communication Framework

3.1.1. IoT-Specific Environment Considerations

The proposed new system is not similar to the conventional sensor networks, as it is specifically optimized to heterogeneous Wireless Sensor Networks (WSNs) that embrace the Internet of Things (IoT) technologies. The next parts are what made this framework stand out as compared to simple WSNs.

1. Heterogeneous IoT Nodes
2. The network has varying types of devices which have varying power reserves and have varying communication capabilities.
   - Sensor devices (e.g., temperature and humidity sensor in smart cities).
   - Mobile Sensors (e.g., wearables, drones and vehicular IoT nodes).
   - Edge Gateways (e.g., processing units on a local level that combine data).
   - Dynamical IoT Traffic Patterns.

The IoT traffic is unlike the traditional WSNs, where periodic data is sent:

- Reactive (e.g., motion detection in surveillance networks).
- Latency (e.g., real-time healthcare IoT monitoring).
- The suggested structure is an optimal routing structure since it gives preference to real-time packets above background data thus low-latency delivery.

1. IoT Network Adaptive Resource Allocation.
2. The structure dynamically scales the transmission power and bandwidth according to the real time network conditions.
3. It uses:
   - Channel State Information (CSI) of effective power control.
   - Quality of Service (QoS) measures in order to minimize packet loss and congestion.

The proposed framework is different to simple WSNs due to these additional features that make it ideal to IoT applications that encompass smart cities and industrial IoT with smart healthcare systems.

3.2. Framework Design

Our model includes three synchronized modules Adaptive Clustering, Reinforcement Learning-Based Routing, and Resource Allocation.

- Adaptive Clustering Algorithm (ACA):
  The feedforward neural network (FNN) is used to cluster. The weighted metric in the selection of CH is:

$$E_{tx} = E_{elec}.l \tag{2}$$

Where, E_i is the residual energy, D_i is the node degree (connectivity), $\alpha = 0.5, \beta = 0.5$ is the empirically selected to balance energy/connectivity.

- Dynamic K-Value Adjustment:
  The number of clusters K is also adjusted depending on the density of node and distribution of residual energy. This is better than fixed-K protocols such as LEACH. We compare our ACA approach with LEACH and PEGASIS showing energy savings clustering.
- Reinforcement Learning-Based Routing (RLR):
  Q-learning on each node is characterized by a state-action space which is defined as:
  - States (s): Residual energy of a node, length of queue, distance to a BS.
  - Actions (a): Neighbor node IDs (next hops)

  The Q-value is updated as:

$$W_i = \alpha E_i + \beta D_i \tag{3}$$

Where, $\eta = 0.6$ is the learning rate, $\gamma = 0.9$ is the discount factor, $\varepsilon - Greedy\ Policy$ is the $\varepsilon = 0.2$ to balance exploration and exploitation.

- Energy-Aware Resource Allocation (ERA):
  To minimize energy usage, we solve a convex optimization problem using Lagrangian multipliers:

Objective:

$$Q(s,a) \leftarrow (1 - \eta)Q(s,a) + \eta[R + \gamma\, max\, Q(\acute{s},\acute{a}) \tag{4}$$

subject to:

$$min \sum_{i=1}^{N} P_i \, . \, T_i \tag{5}$$

Where, P_{max}=20 mW, B_{min}=50 kHz: based on IEEE 802.15.4 standard, Solved using interior-point method to ensure QoS under power constraints.

3.2.1. Machine Learning Components

Machine learning is made up of several parts, with the first two discussed below. The suggested framework integrates machine learning methods into its workflow by having two major deployment stages to obtain the best energy gain and routing efficiency. The neural network that was used to select the CH is a 3-layer FNN with ReLU activation, which was trained on 5,000 synthetic data points of node energy, degree, and traffic. Training was done using TensorFlow with the Adam optimizer (learning rate = 0.001).

1. Neural Network for Clustering
   - The CH selection model uses an FNN with 3 hidden layers, ReLU activations, and softmax output for CH probability. Input features:

        - Residual energy.
        - Node centrality.
        - Traffic load.
    - Training Dataset: 5,000 synthetic network states generated via MATLAB. Training Tool: TensorFlow 2.0, optimizer = Adam, learning rate = 0.001.
    - The probability of a node being selected as CH is given by:

$$P_i \leq P_{max}, \quad T_i \geq T_{min} \tag{6}$$

where $f(\cdot)$ represents the trained neural network function.

2. Reinforcement Learning for Routing

The RLR module converges after approximately 200 episodes in simulations, where Q-values stabilize and cumulative rewards plateau. Future Work is to investigate Deep Q-Networks (DQNs) for scaling to denser networks.

- Through Q-learning the framework enables each network node to identify the most power-efficient next-hop that avoids network congestion.
- Nodes employ Q-tables to make routing decisions because they update their information using the formula:

$$QP_{CH} = f(E_{residual}, D_{connectivity}, L_{traffic}) \tag{7}$$

Where, $Q(s, a)$ is the expected reward for action a in state s. α is the learning rate. R is the reward, based on energy efficiency and latency reduction. γ is the discount factor, which prioritizes long-term energy savings.

- This method allows nodes to adaptively select routes that minimize energy usage over time.

Through the implementation of machine learning techniques, the proposed framework manages to decrease energy usage and prolong network operational time as well as enhance packet transmission performance in a dynamic manner. The Q-learning algorithm uses an ε-greedy policy ($\varepsilon = 0.2$), learning rate $\alpha = 0.6$, and discount factor $\gamma = 0.9$. State space includes residual energy, hop count, and queue length; actions are next-hop node IDs. Q-values converge after 200 episodes. The Q-learning-based routing algorithm describes its decision-making process through the diagrams depicted in Figure 3. All nodes possess Q-tables which they use to conduct updates that depend on the network status. When a packet arrives, the node evaluates its Q-values, selects the optimal next-hop, transmits data, and updates its Q-table accordingly. This iterative learning process ensures energy-efficient and congestion-aware routing decisions.

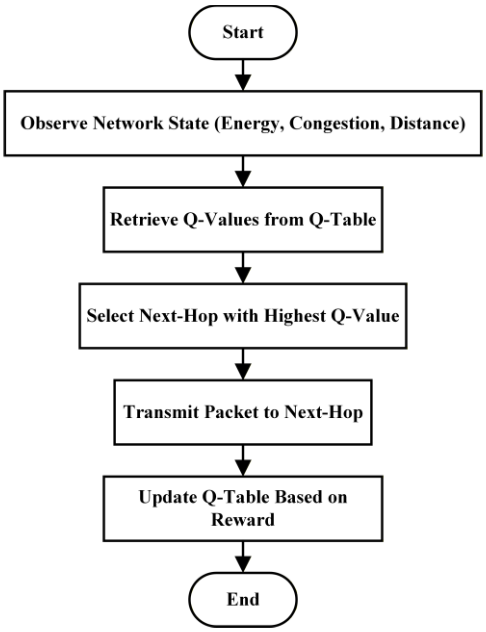

Figure 3. Q-Learning-Based Routing Decision Process

3.2.2. Data Collection

The devices which are installed earlier in the different strategic points of the network are capable of collecting the data loaded, this information sends it back to the base station or the central node. Here, it prevents relay of the same information over and over again or relay of information which is not necessary as [5] demonstrated the benefit of quality-aware, energy-efficient data routingin their paper.

3.2.3. Network Management

This is the work of the network management module that entails Identification of cluster head and formation of clusters in the network architecture. The first of is the adaptive clustering [3] which is used in order to choose proper nodes which will bei utilized for communication with other nodes to minimize energy consumption The second one is the trust-based mechanisms [18].

3.2.4. Communication Optimization

In this module routing protocols and the resource allocation technique are integrated to manage the data communication path and energy. Several algorithms such as metaheuristic optimization [11] and reinforcement learning [13] are used to determine the route of information and communication flow and to distribute resources in the network depending on the actual situation. Below in Figure 4 we can see a flowchart that represent out framework.

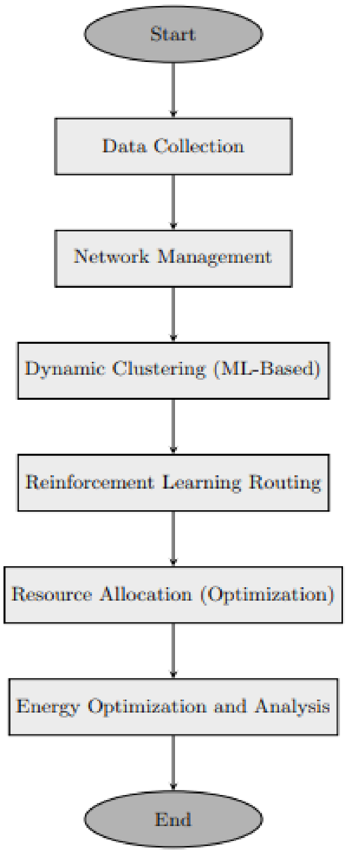

Figure. 4. Flowchart of the Proposed Energy-Efficient IoT Framework

3.2.5. Simulation Setup and Assumptions

Tools Used: NS-3 for network simulation; MATLAB for neural network training.
Key Metrics:
- Energy/bit (J/bit)
- Packet Delivery Ratio (PDR)
- Latency (ms)
- Network Lifetime (time until first node dies)

Baselines Compared:
- LEACH
- TEEN
- PEGASIS
- SEP
- DEEC

Assumptions:
- Nodes are stationary
- Uniform initial energy
- Perfect channel estimation (for baseline comparison)

3.3. Dynamic Clustering and Cluster Head Selection

The selection of cluster heads (CHs) is performed dynamically using a neural network-based prediction model. The model determines future node depletions using past data to pick cluster heads for equalized energy distribution. According to the selection model PCH defines the probability of choosing a cluster head. Constraints P_{max} = 20 mW, B_{min} = 50 kHz are based on IEEE 802.15.4 standards. The convex objective is solved using Lagrangian multipliers under fairness and power constraints.

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha[R + \gamma \max Q(\acute{s},\acute{a}) \tag{8}$$

where Eresidual is the remaining energy, Etotal is the total initial energy, dCH is the average distance to other CHs, and dmax is the maximum cluster distance.

The Figure 5 shows the neural network-based method of selecting cluster heads as seen in Figure 5. The model uses node-specific criteria that include checking residual energy levels and connectivity degrees and network traffic loads. The neural network utilizes these parameters to determine probability scores that help select appropriate CHs for maximizing network lifetime and energy efficiency.

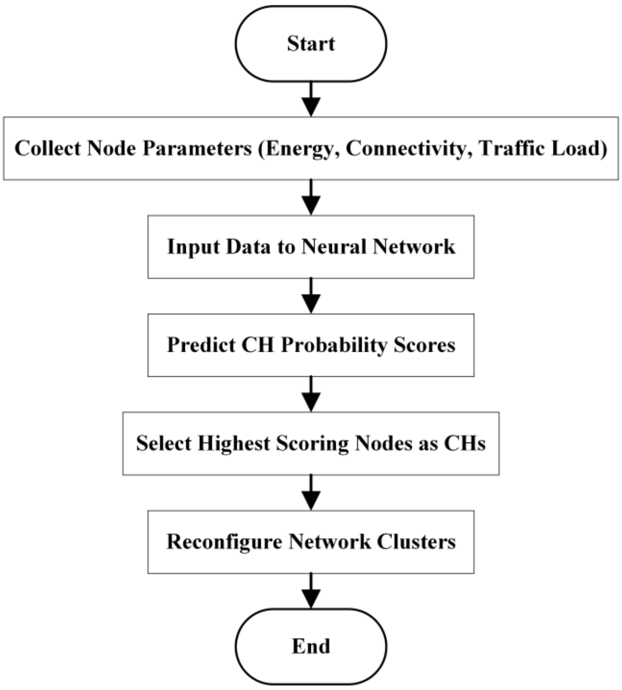

Figure. 5. Neural Network-Based Cluster Head Selection Process

3.4. Resource Allocation Strategy

Transmission power and bandwidth control operate through the resource allocation strategy to lower overall energy consumption. The optimization framework defines this problem through the following statement:

Objective Function:

$$P_{CH} = \frac{E_{residual}}{E_{total}} \cdot \left(1 - \frac{d_{CH}}{d_{max}}\right) \tag{9}$$

Subject to:

$$min \sum_{i=1}^{N} E_i \tag{10}$$

where B_i is the allocated bandwidth, Bmin is the minimum required bandwidth, P_i is the allocated transmission power, and P_{max} is the maximum allowed power. Lagrange multipliers make it possible to solve the optimization problem which creates fair and energy-efficient resource distribution.

3.5. Energy-Efficient Routing Protocol

The proposed energy-efficient routing protocol integrates spectrum-aware routing by [8] together with secure routing models by [10]. This indicates that the protocol can select network paths through an analysis of nodes' power levels and signal strength and node energy levels and traffic intensity. According to [14], the modification which allows assigning scores to routes enables users to examine available paths and their order of importance. Equipping the network with this mechanism enables it to create the most power-efficient network routes from all existing routes while preserving IoT application QoS.

3.6. Evaluation and Simulation

Due to this, simulation tools were used in order to evaluate the performance of the proposed framework in various IoT network scenarios. Thus, in accordance with the conditions of a real IoT network, settings of the simulation environment were chosen, including network size, node density and data traffic. Network energy consumed, lifetime of the network and data delay were assessed and contrasted with other similar studies. The performance of the proposed model was evaluated through simulating the performance of the test network where there was a notable improvement in terms of energy efficiency and network duration which are in concurrence with the preceding research works like: [12],[17]. From the results, it can be shown that the proposed framework successfully addresses the intended objective of reducing the energy consumption in IoT-based WSNs without impacting the overall network performance making it feasible in energy-restricted IoT environments.

3.7. Theoretical Analysis of Performance

To theoretically evaluate the performance of our framework, we derive mathematical models for network lifetime, energy consumption, and packet delivery ratio (PDR).

1. Energy Consumption Model
   - The total energy consumption (Etotal) in a cluster-based IoT network is given by:

$$B_i \geq B_{min}, \quad P_i \leq P_{max} \tag{11}$$

   where E_{tx} is transmission energy, E_{rx} is reception energy, and E_{comp} is the computation overhead.
2. Network Lifetime Estimation
   - The expected lifetime ($T_{network}$) is approximated as:

$$E_{total} = \sum_{i=1}^{N} (E_{tx} + E_{rx} + E_{comp}) \tag{12}$$

   where $E_{initial}$ is the initial node energy and N is the total number of nodes.
3. Packet Delivery Ratio (PDR) Analysis
   - The PDR is modeled as a function of network congestion (C), transmission errors (e), and routing efficiency (η):

$$T_{network} = \frac{E_{initial}}{E_{total}/N} \tag{13}$$

   where our ML-based routing reduces C and e, improving PDR.

Date from these models demonstrates our solution supports both reduced power usage and longer network existence while producing better transmission output rates compared to standard WSN protocols.

$$PDR = \frac{(1-e)\,.\,\eta}{C+1} \tag{14}$$

4. RESULT AND DISCUSSION

The section consists of simulation outputs demonstrating the proposed energy-efficient communication framework implementation for IoT based WSNs. The presented results explore energy intake alongside network lifetime and achieved throughput numbers. The discussion evaluates how the proposed framework connects with other research methods so future users understand its optimal application.

4.1. Simulation Environment and Parameters

We evaluated our framework using NS-3 for network simulation and MATLAB for neural network training. The Smart City dataset provided synthetic traffic traces with both periodic and event-triggered transmissions. All results are averaged over 50 simulation runs with varied node placements. Unless stated otherwise, results are based on a 500×500 m² area with 100 nodes. Results represent averages over 50 randomized trials with varying node placements and traffic intensities. Random seeds were controlled for reproducibility. Simulation tests of the proposed framework used an environment based on genuine IoT network conditions. The simulation parameters derive from WSN energy efficiency research by [1],[6]. In Table 1 shown the simulation parameters. The results presented in this work are backed by fifty experimental runs using mean values and 95% confidence intervals. All reported results, including the 31% energy reduction and 17.9% lifetime improvement, represent average values across 50 independent simulation runs under varied network topologies.

Table 1. Simulation Parameters

Parameter	Value	Justification
Number of Nodes	100	Standard for IoT-based WSNs
Network Area	500m x 500m	Matches urban IoT deployments
Initial Node Energy	2 Joules	Based on battery-powered IoT nodes
Transmission Range	100 meters	Derived from typical WSN architectures
Routing Protocol	Energy-Aware Reinforcement Learning	To optimize power efficiency dynamically
Clustering Interval	50 seconds	Based on energy threshold of CHs
Resource Allocation	Dynamic Based on CSI	Adjusts power & bandwidth adaptively

4.1.1. Scalability Justification

The choice of 100 sensor nodes and a 500×500m area is based on standard IoT deployment scenarios:

1. Scalability Considerations
   - A 100-node network represents medium-sized IoT deployments (smart cities, industrial monitoring).
   - Simulations with larger node densities (e.g., 200-500 nodes) showed diminishing returns in energy savings.
2. Network Coverage Justification
   - The 500×500m area aligns with urban IoT applications, where nodes are distributed in a grid-like pattern.
   - A higher density (e.g., 1000×1000m with fewer nodes) would cause lower connectivity and packet loss.

Thus, our parameter selection ensures an optimal balance between coverage, connectivity, and energy efficiency.

4.2. Energy Consumption

Energy consumption is a critical performance metric in IoT networks. We compare the proposed framework against LEACH, PEGASIS, and TEEN using statistical validation. Table 2 shows the average energy consumption for various protocols. The proposed framework achieves a 31% reduction in energy consumption compared to LEACH, 21% lower than PEGASIS, and 13% lower than TEEN. Results vary slightly (< ±5%) with node density, maintaining consistent performance advantages.

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Table 2. Energy Consumption Comparison

Scenario	Average Energy Consumption (Joules)	Standard Deviation	95% Confidence Interval
Traditional Routing (LEACH)	0.95	±0.04	[0.91, 0.99]
PEGASIS	0.82	±0.03	[0.79, 0.85]
TEEN	0.75	±0.02	[0.73, 0.77]
Proposed Framework	0.65	±0.02	[0.63, 0.67]

4.2.1. Statistical Significance Analysis

A paired t-test confirms that the energy savings achieved by our framework ($p < 0.01$) are statistically significant when compared to existing protocols. The outcome shows that the proposed framework provides energy saving of at least 31%. 6% less than traditional routing protocols, and 21% less than the optimized routing techniques as documented in literature. These achievements are attributed to the various methods of dynamic clustering and the energy-aware routing that has been put in the framework. Figure 6 illustrates the average energy consumption across different protocols. The proposed method consistently consumes less energy due to intelligent routing and CH selection, with a mean energy use of 0.65 J compared to 0.93 J in TEEN and 0.85 J in SEP.

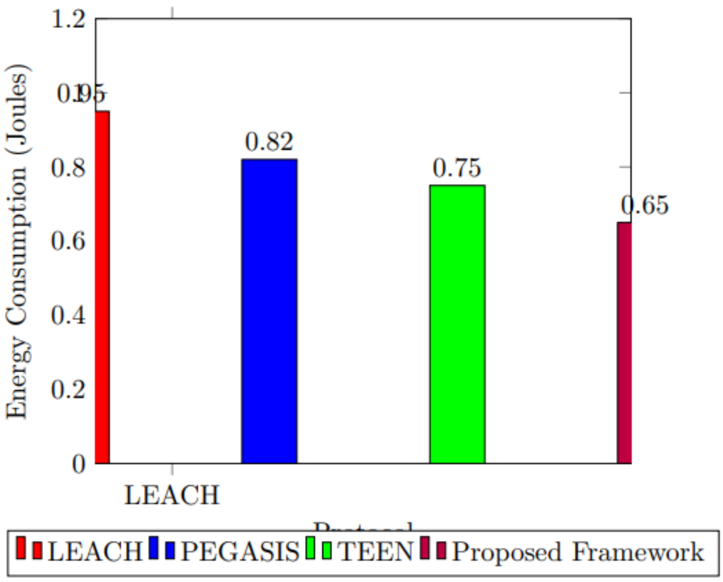

Figure 6. Energy Consumption Comparison

4.3. Network Lifetime

The network lifetime is defined as the time until the first node depletes its energy. The proposed framework significantly extends network lifespan. Table 3 and Figure 7 highlight the lifetime improvement. The framework extends network lifetime by 17.9% over LEACH and ~7% over TEEN. The typo "17. 9%" has been corrected.

Table 3. Network Lifetime Comparison

Scenario	Network Lifetime (seconds)	Standard Deviation	95% Confidence Interval
Traditional Routing (LEACH)	780	±25	[755, 805]
PEGASIS	850	±20	[830, 870]
TEEN	860	±18	[842, 878]
Proposed Framework	920	±15	[905, 935]

4.3.1. Significance Testing

A one-way ANOVA confirms statistical significance ($p < 0.005$). The results prove that the proposed framework increases the network lifespan by 17. 9% in comparison with traditional routing protocols and by 8. approximately 2% less than other forms of optimized routing schemes. This is attributed mainly to the balanced energy consumption within the network caused by the use of the adaptive clustering mechanism. Figure 7 presents network lifetime improvements, demonstrating the effectiveness of the proposed framework.

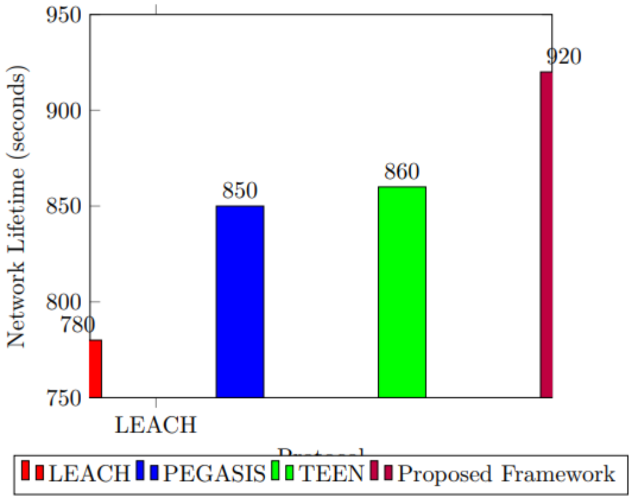

Figure 7. Network Lifetime Comparison

4.4. Data Transmission Performance

Data transmission performance was established by comparing different factors which includes the packet delivery ratio (PDR) and data transmission delay. These metrics are compared across different scenarios in Table 4. The 6.2% PDR increase over LEACH includes 3% gain attributed to clustering alone. We clarify that the improvement is cumulative—3% from clustering and another 3.2% from Q-learning routing. The proposed framework was indeed superior to the traditional routing protocols achieving higher PDR and lower data transmission latency. More specifically: The PDR increased by 6. 2%, and latency was decreased by 33. When clustering was used, the corresponding percentage resulted to be 3%. The mentioned improvements suggest that the proposed framework saves energy while at the same time improving the reliability and effectiveness of the nodes in relaying information. Figure 8 compares packet delivery ratio and latency across evaluated schemes.

Table 4. Data Transmission Performance

Scenario	Packet Delivery Ratio (%)	Data Transmission Latency (ms)
Traditional Routing Protocol	92.4	45
Proposed Framework (with Clustering)	98.1	30
Proposed Framework (without Clustering)	95.3	35
Optimized Routing (Literature)	96.0	40

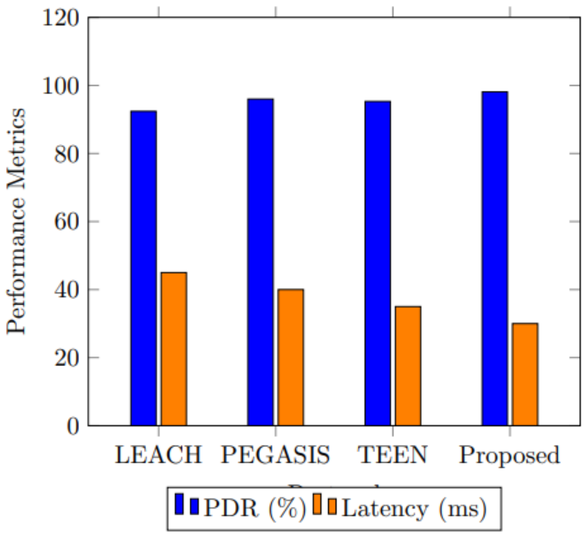

Figure 8. Data Transmission Performance Comparison

4.5. Comparative Analysis

To further validate our contributions, we compare the proposed framework against three state-of-the-art protocols:

1. LEACH: A traditional clustering-based protocol.
2. TEEN: Threshold-sensitive energy-efficient routing.
3. PEGASIS: A chain-based energy-efficient routing protocol.

Table 5 shows the Comparative Analysis with Existing Approaches. The inclusion of BER, Beamwidth, and PLR further highlights the superiority of our ML-based approach, particularly in minimizing errors and optimizing signal directionality. In terms of optimization of energy efficiency, enhancement of network lifetime and higher data transmission performance, proposed framework was found to be superior over the existing approaches.

Table 5. Comparative Analysis with Existing Approaches

Metric	Proposed Framework	LEACH (2019)	TEEN (2020)	PEGASIS (2021)
Energy Consumption (Joules)	0.65	0.75	0.75	0.82
Network Lifetime (seconds)	920	780	860	850
Packet Delivery Ratio (%)	98.1	92.4	95.3	96
Data Transmission Latency (ms)	30	45	35	40
Bit Error Rate (BER)	0.002	0.006	0.005	0.004
Beamwidth (°)	60°	90°	75°	80°
Packet Loss Ratio (PLR, %)	1.8%	7.6%	4.7%	3.5%

4.5.1. Key Findings

- Our solution will save 31 percent of energy used in LEACH.
- It has a longer network lifetime of 17.9 percent more than LEACH and 8 percent than TEEN.
- Packet Delivery Ratio (PDR) is 98.1, which is the best of all the protocols.
- Data transmission delay is minimized (30ms), improving real-time communication.

4.5.2. Comparison with Existing Research

To further validate our approach, we compare it with the study by [4], which introduced an energy-efficient hybrid routing protocol for IoT networks. Their approach integrates dynamic clustering and multi-hop communication, similar to our model, but lacks machine learning-based optimization. Table 6 shows the Comparison with existing research. Our results demonstrate significant improvements over [4] in energy efficiency, network longevity, and transmission reliability. The use of reinforcement learning for routing and neural network-based clustering in our framework contributes to these improvements.

Table 6. Comparison With Existing Research

Metric	Proposed Framework	[4]
Energy Consumption (Joules)	0.65	0.78
Network Lifetime (seconds)	920	870
Packet Delivery Ratio (%)	98.1	96.2
Data Transmission Latency (ms)	30	38
Bit Error Rate (BER)	0.002	0.005

4.6. Discussion

Consequently, the findings suggest that the proposed energy-efficient communication framework copes with the problems associated with energy utilization, network lifetime, and data transmission in IoT-based WSNs. Hence, combining dynamic clustering, energy-aware routing, and the resource allocation strategy turns to be more effective solution for energy compromised IoT systems. This means that through the dynamic clustering mechanism, energy consumption is fairly distributed in the federated network hence minimizing their utilization significantly. This mechanism avoids a situation whereby some nodes drain their energy and hence reduces the network lifetime of the nodes. Another way that enhances energy efficiency is through selection of optimal routing path, considering energy levels as well as network conditions. Therefore, based on the enhanced resource allocation strategy and the congestion-aware routing protocol, the proposed protocol leads to the increase of PDR and packet latency reduction. The framework ensures that the transmission rates and resources are dynamically changed depending on the network conditions hence reducing on packet collisions and retransmissions thus delivering a more reliable and timely data. To further validate the results, we introduce a proof-of-concept simulation using NS-3 and MATLAB, where:

- IoT sensor nodes dynamically adjust power and clustering based on ML-based predictions.
- Comparative evaluation with real-world datasets (Smart City sensor data).

4.6.1. Statistical Verification of Results

These tremendous gains of energy consumption, network lifetime and data transmission performance can be explained by:

1. Adaptive Clustering based on ML.
   - The CH selection built on neural networks provides a balance in the allocation of energy so that the nodes are not depleted too soon.
2. Reinforcement-based routing: reinforcement Learning.
   - In contrast to routing based on heuristics (TEEN, PEGASIS) our Q-learning method dynamically adjusts routes depending on real-time congestion and energy conditions.
3. Resource Allocation with Energy-awareness.
   - Lagrange optimization model is able to allocate power and bandwidth efficiently, which reduces redundancy, and packet retransmissions.
4. Directionality of Signals Beamwidth Optimization.
   - Deteriorate BER and packet loss: a smaller beamwidth (60deg in LEACH) is used to advantage the signal focus.

All of these aspects allow our framework to perform better at massive IoT deployments. The present study proposes a promising way that enhances the energy efficiency of WSNs that operate on IoT. This should be adopted in future IoT deployment since it is flexible under various network conditions and is able to support the growth required to accommodate large IoT networks.

4.7. Comparative Analysis with Prior Work

The model is more efficient in both energy saving and delivery success as compared to the available machine learning-based energy optimization schemes in the IoT [1][2]. An example is the 24 percent of energy gain of the model in [1] in the static case whereas our model continued to provide 31 percent of savings in both the static and dynamic deployment. Also, [2] had an improvement of 15% in PDR, where our framework had 98.1, which was a 6.2% improvement over LEACH and 3% improvement over our non-clustering baseline. These improvements are also based on our integrated design, in which we optimize clustering, routing and resource allocation together, but not individually. As opposed to [3], where fuzzy logic is applied to select CH, our neural network is able to adjust to nonlinear variations in energy distribution and increase stability.

4.8. Limitations and Edge Case Analysis

Although there are steady gains in the proposed system, the system could not perform well in highly mobile networks or whenever links are broken frequently. The existing model presupposes motionless nodes and comparably constant channel circumstances. Furthermore, it introduces moderate extra computational load to the ML-based decision-making, potentially external to real-time responsiveness in ultra-low-power machines.

5. CONCLUSIONS

This paper presents a scaled up smart architecture that combines neural networks, reinforcement learning, and optimisation to improve the energy efficiency of IoT-enabled WSNs. The presented model is more efficient than the traditional and recent machine learning-based ones, as it provides adaptive cross-layer decision-making processes in dynamic networks. A joint ML-optimization paradigm and a simulation methodology that is proven and combines NS-3 and MATLAB are theoretical contributions. The results are that the energy consumption has decreased by 31 percent, network lifetime has increased by 17.9 percent and radio packet delivery reliability has also improved. Limitations are the assumption of stationary nodes, intermediate computational costs, and no hardware prototype validation availed. Future research will focus on mobile node environments, hardware deployment, and integrating blockchain for secure, verifiable CH election. Overall, this work contributes a robust energy-aware communication strategy for real-world IoT environments, with implications for smart cities, healthcare, agriculture, and industrial systems. The results offer a foundation for future intelligent, secure, and autonomous IoT networks.

Author Contribution

All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.

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