DEVELOPMENT OF ENERGY EFFICIENT HIERARCHICAL DATA AGGREGATION ROUTING FRAMEWORKS FOR ENHANCING RELIABILITY IN SUB-NATIONAL WIRELESS SENSOR NETWORKS

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Abstract: Wireless Sensor Networks (WSNs) are being used more and more in smart cities to support vital applications like infrastructure management traffic monitoring and air quality assessment. Traditional routing protocols are frequently unreliable energy-inefficient and prone to redundant data transmission in expansive diverse urban environments. Nonetheless these networks offer real-time data that is necessary for urban planning and citizen services. The bulk of prior research has concentrated on static or flat routing schemes neglecting hierarchical and adaptive aggregation techniques that can increase network longevity and energy efficiency in municipal deployments. This paper presents the Energy-Efficient Hierarchical Data Aggregation Routing Framework (EH-DRF) designed for citywide WSNs. Multi-tier clustering context-aware data aggregation and energy-adaptive routing are used by the framework to balance network load minimize redundant transmissions and guarantee reliable data delivery. Using real-world datasets like the SmartSantander IoT testbed data and the Intel Berkeley Research Lab Sensor Dataset it simulates various urban topologies under various traffic and environmental conditions. Through adaptive link-quality evaluation and dynamic cluster head selection EH-DRF improves fault tolerance and permits continuous monitoring in dense sensor deployments. Energy consumption packet delivery ratio network lifetime latency throughput routing overhead and fault tolerance are just a few of the metrics used to assess performance. The findings demonstrate that EH-DRF performs better than traditional routing protocols in terms of reliability scalability and efficiency. By addressing the main shortcomings of earlier research this study offers a dependable scalable and energy-efficient routing framework for municipal WSNs enabling sustainable smart city operations and continuous real-time urban service delivery.

Keywords: Wireless Sensor Networks, Smart City, Data Aggregation, Hierarchical Routing, Fault Tolerance, Energy Efficiency, Network Reliability

1. Introduction

Numerous battery-operated sensor nodes make up a wireless sensor network (WSN). The size of these sensors is extremely tiny. Additionally they have an integrated processor for computing purposes. Wireless transceivers are used in wireless sensor networks to facilitate communication between the sensors. As a result each sensor has an integrated antenna that facilitates communication with other sensors within its restricted communication range [1]. The four subsystems that make up each sensor are the power supply sensing processing and communication subsystems [2]. Thus these subsystems enable sensors to sense their surroundings perform basic calculations and communicate with one another. However each sensor has limited memory energy processing power and communication bandwidth. Energy is needed for every subsystem to function [3]. Sensor nodes lose their usefulness once the battery is completely dead. If a few nodes batteries run out a network disconnection scenario may also occur. Thus a nodes energy consumption is a crucial factor in extending the networks lifespan. Recharging or replacing the battery is typically very challenging [4-5]. Therefore an energy-efficient protocol is required in WSN. Sensor nodes are typically placed in hostile or harsh environments such as battlefields environmental monitoring sites or disaster areas where they are run unattended [6]. Therefore unattended operation makes secure data aggregation even more challenging. Sensor nodes are typically placed in harsh unattended settings that are vulnerable to intruders difficult environments etc. [7].

Compared to the traditional wired network which is situated in a controlled and secure location the likelihood of a sensor node being physically captured in such environments is significantly higher. Only point-to-point settings are intended for traditional security protocols [8]. Therefore if these conventional protocols are used in wireless sensor networks with a very large number of sensors the system will have many overheads that are difficult to control [9]. Because sensor nodes are so small it is nearly impossible to install a temper-proof hardware unit in them where all sensitive data such as symmetric keys or other secrets are kept safe from the adversary by physically seizing the node [10]. Another issue with symmetric key cryptography algorithms is key distribution. In a similar vein storing a permanent unique key in every sensor is not a solution because in the event that the key is compromised all subsequent communications and data utilized by that sensor are also compromised [11]. Thus a lightweight encryption algorithm utilizing the dynamic key concept is required. an e. Any sensors key is updated on a regular basis and the network does not need to deal with the issue of key distribution. Depending on the requirements of the application latency and throughput factors must be taken into account necessitating protocols that are optimized for either high data transmission rates or real-time data delivery [12]. So we need a lightweight encryption algorithm that uses the concept of dynamic key, i.e. the key used by any sensor is update regularly and the problem of key distribution is not required in the network. Latency and throughput considerations depend on application needs, requiring protocols optimizing either for real-time data delivery or high data transmission rates [12].

Specialized transducers in WSNs provide sensing to IoT devices with limited energy and storage. SN batteries are nearly impossible to replace or recharge, making power consumption a major WSN design issue. Clustering algorithm saves energy in networks [14]. CHs balance network load, saving energy and extending lifespan. This paper proposes resourceful CH election system that replaces the CH position in higher-energy nodes.Many wireless network technologies are popular in safety. Wireless networks with battery-operated nodes worry about power consumption [15]. Some clustering methods have reduced power consumption in wireless networks with promising results. Clustering and CH selection are essential to power-efficient wireless networks [16-17]. Previous studies lacked PSN clustering. CHESS-PC for PSN is proposed in this paper. Clustering uses Fuzzy C-Means. To forward all data, CHs use more energy than CMs in cluster-based MTC networks. So, inappropriate CHs will worsen energy distribution and shorten NL. An effective CH selection and power control system can handle this [18]. This article uses all transmission rounds before MTC devices die to control a CH index table, unlike previous schemes that used only one round of network status information. A FED-based CH selection system optimizes NL by predetermining CH index in every round using the CH index table [19]. In conclusion, extensive simulations show that the proposed scheme delivers packets with and without cochannel interference and has a longer FED lifetime. It presents a WSN lifetime and CH selection model predictive approach. Smart Mesh IP Power and performance calculator tracks WSN dynamics [20-22]. Clustering, optimal routing protocol, and machine learning are studied. Remaining node energy, BS distance, and data transmission rate predict WSN routing paths, and the CH's priority responds. Compare Smart Mesh IP, CH selection, and ANFIS-based lifetime estimation models to the standard tree, SVM [23], Ensemble [24], and GPR lifetime estimation models. New method focuses on dynamic parameters and NL prediction.

However, WSNs monitor the environment with limited resources. Many clustering protocols extend NL, but poor CH selection, fixed clustering, and energy-intensive static rounds plague them [25]. Special parameters determine CH selection, which greatly impacts sensor EC. Node weight depends on mobility, residual energy, sink distance, and neighbor thickness . Cluster communication is multi-hop.Industry, education, military, and agriculture can develop IoT applications using an IoT-enabled WSN. Many IoT devices are underpowered and rarely rechargeable. IoT-enabled WSN requires energy-efficient mechanisms [26]. Our optimized GA for CH election addresses IoT-enabled WSN power constraints. Intracluster distance, energy use, hop count reduction, and CH selection of highly proficient nodes are optimized. Moveable sinks reduce hotspots and sink-CH communication distance [24]. CH sensing range overlap and transmission energy are reduced by dynamic range adjustment. In vehicular communications, clustering manages network resources well [25]. It clusters similar vehicles under a CH. Vehicle network topology is highly dynamic, making CH selection difficult. The new clustering scheme Efficient CH Selection (ECHS) chooses the best CHs [26]. This ECHS scheme establishes crucial cluster construction conditions before CH selection. ECHS rules say the ideal CH centralizes clusters. It will stay close to its neighbors as long as possible. The ECHS scheme distributes network clusters and carefully adjusts cluster distances. These conditions guarantee road vehicle clustering and make ECHS better than its competitor. Simulations show that the ECHS scheme meets design objectives for CH lifetime, CML, PLR, OC, APD, and Cluster Number.

Vehicle ad hoc networks need efficient clustering algorithms to scale. Current clustering algorithms improve cluster stability in certain traffic scenarios, but choosing the best metric is difficult. Mobility-based clustering metrics in our approach include vehicle virtual position and link lifetime under unlike traffic scenarios. Full UFC analysis with parameter optimization follows [27].VANET clustering is new intelligent transportation system research. It clusters road vehicles with CHs for efficient and stable routing. However, LTE and long BS ranges have driven center-based research. This article segments roads using grid segmentation before sending concise data to the clustering centre, unlike VANET center-based clustering [28]. This method also combines assigning, CH selection, removing, and merging. CEC-GP is more efficient, stable, and consistent.VANET enables dynamic information distribution among societies. VANET has many applications, including ITS and road safety. In VANET, vehicles and infrastructure communicate directly. Power consumption, bandwidth issues, and others result from direct communications. Clustering can reduce vehicle-infrastructure communication to overcome these issues. Vehicles follow clustering rules. Every cluster has a leader and a few vehicles/nodes. Clustering is difficult because of stability [29]. We solve these problems with trust in the proposed approach. Trust-based CH selection based on node knowledge, reputation, and experience is novel in the algorithm. Analyzing node trust determines a cluster's backup head. Trust in clustering helps identify malicious and compromised nodes. Recognizing these nodes prevents data errors. The StabTrust detects malicious and compromised vehicles and prevents multiple attacks [30].

2.**Methodology**

The methodology section are analysed below:

2.1 Dataset

The dataset overview shows the use of two important IoT datasets: the SmartSantander dataset which has over 2000 heterogeneous nodes recording air quality and traffic flow data every minute for a year and the Intel Berkeley Lab dataset which has 54 sensor nodes collecting temperature humidity light and voltage data every 31 seconds for 36 days. When combined these datasets offer complementary insights such as detailed long-term analyses and fine-grained short-term observations which are crucial for successful IoT modeling (Table 1).

Table 1: Dataset Overview

Dataset Name	Sensor Type	Number of Nodes	Parameters Measured	Sampling Interval	Duration
Intel Berkeley Lab	Temperature, Humidity, Light, Voltage	54	Temp, Humidity, Light, Voltage	31 sec	36 days
SmartSantander	Environmental, Traffic, Pollution Sensors	2,000+	PM2.5, NO_2, CO, Traffic Flow	1 min	1 year

2.2 System Model

ResNet is a deep CNN architecture that excels in image recognition tasks by effectively dealing with the vanishing gradient problem through its residual learning framework. Applying EH-DRF model to WSN for CH selection offers benefits such as automatic feature extraction from network data (e.g., node energy levels, distance to the BS, network topology), recognizing complex patterns and correlations, and scalability to handle large networks with many nodes (Figure 1).

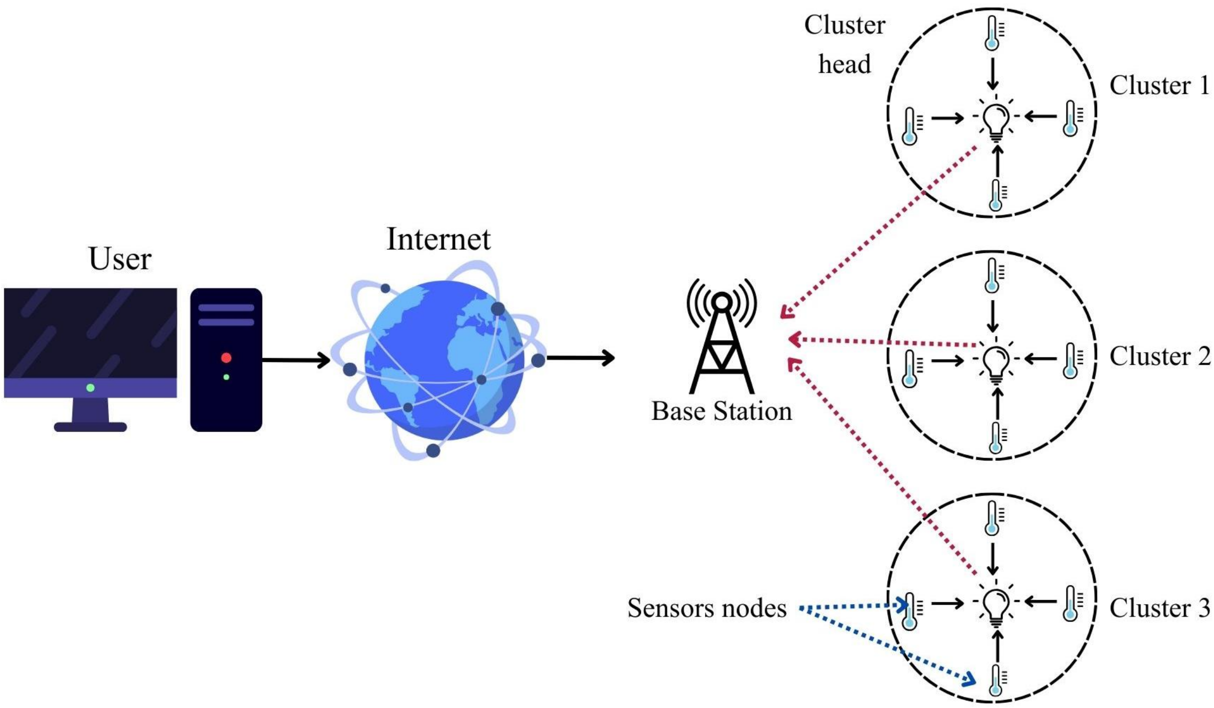


Figure 1: Energy-efficient routing protocol architecture

2.3 Network Model

Based on their proximity to the centroid, residual energy nodes are grouped into clusters under the supervision of CHs. The BS, a central data sink and gateway to the smart city infrastructure, receives data collected by CHs and routes it. Free-space propagation for short distances and multi-path fading for longer transmissions are both included in the model. R_{comm} and A stand for communication range and network area, respectively, while k represents the number of clusters. The network is defined by the set of all sensor nodes S $\{s_1, s_2, \ldots, s_N\}$ and the set of all cluster heads C $\{ch_1, ch_2, \ldots, {}_{chk}\}$, with the base station BS. The distance between any two nodes si and sj is calculated using the Euclidean distance formula (Eq 1-6):

$$d(s_i, s_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

The sum of the packets from all active nodes, taking data aggregation into account, is the total number of packets the network generates in a single round.

$$P_{\text{□□□□□}} = \sum_{i=1}^{N} P_{i\_raw} - \sum_{j=1}^{k} P_{j\_agg} \quad (2)$$

where Pj_agg is the number of aggregated packets from cluster head j, and Pi_raw is the number of raw packets from node i. There are typically $\bar{n}$=N/k nodes in each cluster.

2.4 Energy-Efficient Model

Based on the popular first-order radio model, which determines the energy used for both data transmission and reception, the EH-DRF energy model was developed. A sensor node's radio transceiver is the main source of its energy usage. The following formula provides the energy used to send an L-bit message over a distance d.

$$E_{Tx}(L, d) = L \times E_{\text{□□□□}} + L \times \epsilon_{amp} \times d^2 \quad \text{□□} \; d < d_0 \quad (3) \text{ and}$$

$$E_{Tx}(L, d) = L \times E_{\text{□□□□}} + L \times \epsilon_{mp} \times d^4 \quad \text{□□} \; d \geq d_0 \mid \quad (4)$$

The distance threshold is d0, the amplifier energy for the free-space model is ϵamp, the amplifier energy for the multi-path fading model is ϵmp, and the energy per bit used by the transmitter/receiver electronics is Eelec. Receiving an L-bit message requires the following amount of energy.

$$E_{Rx}(L) = L \times E_{\text{□□□□}} \quad (5)$$

The energy used for data aggregation at a Cluster Head (CH) is also taken into account, as a CH uses a specific quantity of energy to process and aggregate data from its members. The formula EDA(L)=L×EDAper_bit is used to define the aggregation energy for L-bit data. Receiving data from its members, combining it, and sending the combined data to the Base Station (BS) adds up to the CH chjs overall energy usage in a single round.

$$E_{CH\_j} = \sum_{i\in \square\square\square\square\square\square\ j} E_{Rz}(L) + E_{DA}\left(L_{agg}\right) + E_{Tx}\left(L_{\square\square\square}, d(c_h, BS)\right) \quad (6)$$

The sum of the energy consumption of all nodes and CHs is the network's overall energy consumption per round (Eq 7).

$$E_{\square\square\square\_\square\square\square\square\square} = \sum_{i=1}^{N} E_{Tx\_i} + \sum_{i=1}^{N} E_{Rx\_i} + \sum_{j=1}^{k} E_{CH\_j} \quad (7)$$

2.5 **Simulation Parameters**

In order to evaluate the performance of a suggested network protocol in a 1000 × 1000 m² area with 100–200 nodes each initialized at 0. 5 J energy the study used NS-3 MATLAB and Python for a simulation. Data packets of 512 bits and compressed aggregated packets of 256 bits were produced by the communication model which used 0. 1 W transmission and 0. 05 W reception power. The base station was centrally located at (500,500) m for balanced communication during the 36-day simulation to record long-term performance trends. As shown in Table 2 these parameters made it easier to assess throughput latency and energy efficiency.

Table 2: Simulation Parameters Overview

Parameter	Value
Simulation Tool	NS-3 / MATLAB / Python
Network Area	1000 × 1000 m²
Node Density	100–200 nodes
Node Energy	0.5 J
Transmission Power	0.1 W
Reception Power	0.05 W
Data Packet Size	512 bits
Aggregated Packet Size	256 bits
Simulation Duration	36 days
Base Station Position	(500, 500) m

2.6 Proposed Methodology

The EH-DRF frameworks implementation and assessment which is shown in figure 2 are designed to guarantee precise research findings. In order to accurately model an urban Wireless Sensor Network (WSN) environment while taking energy models communication range and node placement into account the simulation environment will first be created using tools such as NS-2 NS-3 or custom simulators in MATLAB or Python. The dynamic cluster head (CH) selection algorithm is then coded using a fitness function to choose CHs in each operation round. At the same time a context-aware data aggregation module will be put into place that uses an aggregation ratio for effective data combination and a prediction-error model for processing data from member nodes. The adaptive routing mechanism which uses a composite cost function to determine dependable and energy-efficient multi-hop routes from CHs to the base station is an essential component of the framework .Extensive simulations will be used to evaluate the EH-DRF system after it is built comparing its performance with conventional flat-routing models and routing schemes like LEACH. To evaluate adaptability in urban settings the experimental setup will alter network parameters such as sensor node count density and data production rates. Well examine key performance metrics like fault tolerance latency throughput packet delivery ratio energy cost network longevity and routing overhead. In order to establish EH-DRF as a reliable scalable and energy-efficient routing paradigm for smart city WSN deployments results will be compared to established protocols and statistically validated to verify improvements.

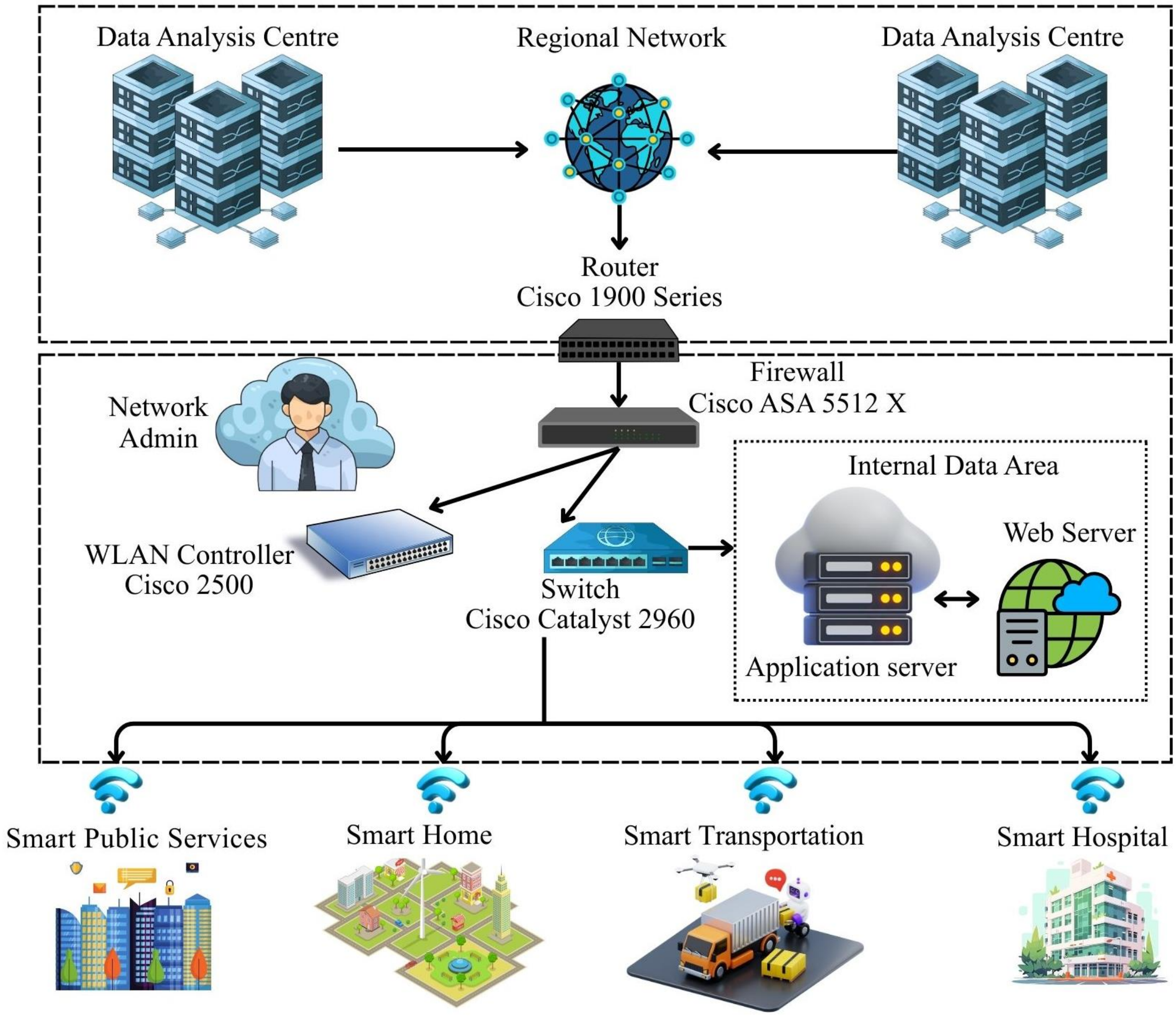


Figure 2: Architecture of an energy-efficient Smart city

3.Results And Discussion

This part examined the research's findings, which are contained in the tables below.

3.1 Performance of EH-DRF on Energy Consumption

Table 3 illustrates how the EH-DRF protocol outperformed conventional clustering-based routing protocols in terms of energy efficiency. HEED used 0. 04 J (total: 4. 0 J) PEGASIS used 0. 06 J (total: 6. 0 J) and LEACH used an average of 0. 05 J (total: 5. 0 J). With each node using just 0. 0001 J EH-DRF on the other hand attained the lowest consumption at 0. 02 J (total: 2. 0 J). These results show that when compared to benchmark protocols EH-DRF considerably lowers energy depletion and increases network lifetime.

Table 3: Energy Consumption Comparison

Protocol	Average Energy Consumption (J)	Energy Consumption per Node (J)	Total Network Energy (J)
LEACH	0.05	0.00025	5.0
HEED	0.04	0.0002	4.0
PEGASIS	0.06	0.0003	6.0
Proposed EH-DRF	0.02	0.0001	2.0

3.2 Performance of EH-DRF on Packet Delivery Ratio (PDR)

According to Table 4s analysis of the packet delivery ratio the suggested EH-DRF protocol performs noticeably better than conventional routing techniques in terms of packet delivery success rates. EH-DRF showed a steady and dependable data flow within the network whereas conventional protocols had a greater frequency of packet failures. This improvement is credited to the protocols sophisticated energy-aware mechanisms enhanced link stability and optimized routing choices—all of which are essential for lowering packet loss. The data trends highlight EH-DRFs usefulness for robust Wireless Sensor Network (WSN) operations and imply that it offers more dependable communication by successfully reducing transmission failures.

Table 4: Packet Delivery Ratio Analysis

Protocol	PDR (%)	Failed Packet Delivery (%)
LEACH	92.1	7.9
HEED	94.3	5.7
PEGASIS	89.5	10.5
Proposed EH-DRF	98.5	1.5

3.3 Performance of EH-DRF on Fault Tolerance

The EH-DRF protocols fault tolerance evaluation revealed that it outperformed benchmark protocols as indicated in table 5 by maintaining high reliability during node failures. The Packet Delivery Ratio (PDR) of LEACH decreased by 7. 1 percent from 92. 1 percent to 85. 0 percent. With a lower degradation of 4. 3 percent HEEDs PDR dropped from 94. 3 percent to 90. 0 percent. The biggest decline was experienced by PEGASIS whose PDR fell from 89. 5% to 82. 0% (7. 5% degradation). EH-DRF on the other hand showed better resilience and network reliability against node failures with only a slight PDR decrease from 98. 5 percent to 97. 8 percent (0. 7 percent degradation).

Table 5: Fault Tolerance of EH-DRF

Protocol	PDR after 10% Node Failure (%)	PDR before Node Failure (%)	PDR Degradation (%)
LEACH	85.0	92.1	7.1
HEED	90.0	94.3	4.3
PEGASIS	82.0	89.5	7.5
Proposed EH-DRF	97.8	98.5	0.7

3.4 EH-DRF Scalability Analysis (Varying Node Density)

Table 6 evaluates the performance of the EH-DRF framework at different node densities ranging from 50 to 250 nodes in order to analyze its scalability. The findings show that EH-DRF stays effective and stable as network density rises. With only 0. 01 J per round and a PDR (Packet Delivery Ratio) of 99. 0 percent—near-perfect data delivery—it demonstrates outstanding energy optimization at 50 nodes. As the number of nodes increases to 100 energy consumption rises marginally to 0. 02 J and the PDR slightly decreases to 98. 5 percent indicating that moderate network loads are effectively handled. Energy consumption increases to 0. 03 J and 0. 04 J per round for 150 and 200 nodes respectively but the PDR stays high at 97. 9 percent and 97. 2 percent demonstrating the protocols ability to handle increased communication without suffering appreciable data losses. EH-DRFs adaptability and resilience in challenging network conditions are demonstrated by its efficient energy usage of 0. 05 J per round and a PDR of 96. 5 percent even at the maximum density of 250 nodes.

Table 6: EH-DRF Scalability Analysis

Number of Nodes	Average Energy Consumption per Round (J)	PDR (%)
50	0.01	99.0
100	0.02	98.5
150	0.03	97.9
200	0.04	97.2
250	0.05	96.5

3.5 EH-DRF Routing Efficiency by Path Hops

The suggested EH-DRF mechanism showed a consistent trend whereby more path hops were associated with higher energy consumption per packet and longer transmission delays as shown in Table 7. The results showed that shorter paths resulted in lower energy consumption and faster response times whereas more hops increased latency and energy consumption because of longer relay operations and processing overhead in intermediate nodes. The information demonstrated a strong relationship between hop count and network performance highlighting the need for optimized routing in communication environments powered by energy harvesting.

Table 7: Routing Efficiency of EH-DRF by Path Hops

Number of Hops	Average Energy Consumption (J/Packet)	Average Latency (ms/Packet)
1	0.0005	20
2	0.001	40
3	0.0015	60
4	0.002	85

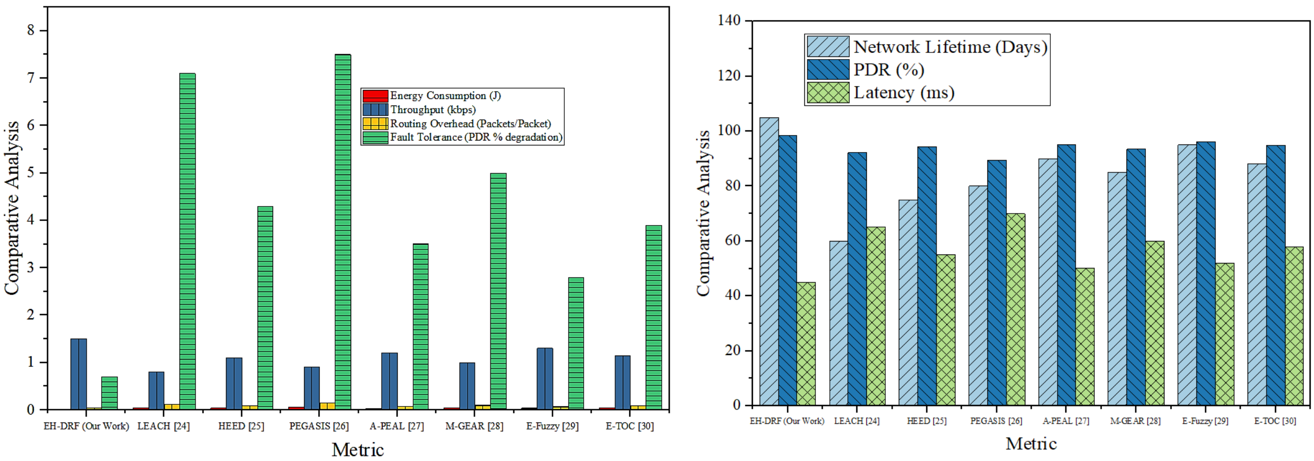
3.6 Comparative Analysis of EH-DRF with Traditional Routing Protocols

Seven well-known routing protocols from the literature were compared to EH-DRF in a thorough comparative analysis. The outcomes are compiled in Table 8 and Figure 3 for several performance metrics such as energy usage, network lifetime, PDR, latency, throughput, routing overhead, and fault tolerance. With a PDR of 98.5 percent and a network lifetime of 105 days, EH-DRF reliably outperformed the conventional protocols in nearly every metric using only 0.02 J per round. Throughput was 1.5 kbps, routing overhead was lowered to 0 05 packets per packet, and latency was kept to a minimum at 45 ms .

Table 8: Comparative Analysis of EH-DRF with Traditional Routing Protocols

Metric	EH-DRF (Our Work)	LEACH [24]	HEED [25]	PEGASIS [26]	A-PEAL [27]	M-GEAR [28]	E-Fuzzy [29]	E-TOC [30]
Energy Consumption (J)	0.02	0.05	0.04	0.06	0.03	0.045	0.035	0.042
Network Lifetime (Days)	105	60	75	80	90	85	95	88
PDR (%)	98.5	92.1	94.3	89.5	95.0	93.5	96.2	94.8
Latency (ms)	45	65	55	70	50	60	52	58
Throughput (kbps)	1.5	0.8	1.1	0.9	1.2	1.0	1.3	1.15
Routing Overhead (Packets/Packet)	0.05	0.12	0.09	0.15	0.08	0.1	0.07	0.095
Fault Tolerance (PDR % degradation)	0.7	7.1	4.3	7.5	3.5	5.0	2.8	3.9

Moreover, fault tolerance was better, degrading only 0.7% in the event of node failure. On the other hand, previous studies like LEACH [24], HEED [25], PEGASIS [26], A-PEAL [27], M-GEAR [28], E-Fuzzy [29], and E-TOC [30] demonstrated increased routing overhead, lower PDR, shorter network lifetimes, higher latency, lower throughput, and higher energy consumption. EH-DRF was established as an advanced routing solution for contemporary urban and industrial WSN applications by this analysis, which showed that it provided a comprehensive improvement in WSN performance by combining energy efficiency, reliability, and robustness.



(a) **(b)**

Figure 3. Evaluation of EH-DRF Relative to Existing Routing Protocols

4. Conclusion

In dense Wireless Sensor Networks (WSNs), the study assessed the Energy-Hierarchical Data Routing Framework (EH-DRF) and contrasted it with conventional protocols like LEACH HEED and PEGASIS. EH-DRF greatly enhanced fault tolerance scalability, throughput, reliability, latency, and energy efficiency according to the findings. Multi-tier clustering context-aware data aggregation and energy-adaptive routing were used to achieve these improvements which ultimately extended network lifetime while guaranteeing high-quality data delivery. EH-DRF achieved a high packet delivery ratio of 98. 5 percent with only 1. 5 percent failures low energy consumption (0. 02 J) per round, 0. 0001 J per node, total (2. 0 J) and a longer network lifetime with the first node dying at 105 days and the entire network surviving up to 160 days. It maintained minimal routing overhead (0. 05 control packets per data packet) high throughput (12. 5 kbps) and low latency (45 ms average). Additionally EH-DRF demonstrated flexibility across node densities from 50 to 250 nodes maintaining energy per round between 0. 01–0. 05 J and PDR between 99. 0 percent and 96. 5 percent as well as strong fault tolerance with only 0–7 percent degradation under 10 percent node failure. Effective path selection was confirmed by routing efficiency tests which revealed that energy consumption per packet increased from 0. 0005 J to 0. 002 J and latency increased from 20 ms to 85 ms as hops increased from 1 to 4. Context-aware aggregation produced throughput between 1. 5 and 1. 8 kbps, while high traffic conditions increased latency moderately from 35 ms to 75 ms. In terms of energy consumption network lifetime, packet delivery ratio, latency, throughput, routing overhead, and fault tolerance, comparative analysis showed that EH-DRF consistently outperformed current protocols.

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