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Research Article

Keywords: Wireless sensor networks, Energy-efficient routing, Internet of Things, Hierarchical clustering Quantum-inspired optimization.

Posted Date: April 9th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8676564/v1

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Additional Declarations: No competing interests reported.

Energy-Balanced Hierarchical Routing for Monitoring and Industrial IoT Applications in Dense Wireless Sensor Networks

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Abstract

The quick growth of large-scale Internet of Things (IoT) deployments has made it even more important for high-density wireless sensor networks (WSNs) to have stable and energy-efficient routing mechanisms. Traditional hierarchical routing protocols use linear, probability-based methods to choose cluster heads (CHs). These methods often cause random energy imbalance and early network fragmentation. This paper suggests an Advanced Quantum-Adaptive Hierarchical Routing (A-QAHR) protocol that uses a quantum-inspired stochastic tunneling (QST) mechanism for non-linear CH selection to get around these issues. The proposed model sees the energy left in a node as a dynamic state variable and uses quantum barrier logic to move CH duties away from nodes that need energy. A new cross-layer entanglement factor considers residual energy, node density, and distance to the sink to make sure that energy is used up evenly and routing is more stable. The proposed protocol was evaluated using Monte Carlo simulations implemented in MATLAB R2021a and comparing its results to those of state-of-the-art protocols like LEACH, SEP, and DEEC. The simulation results show that A-QAHR increases the stability period (the first node to die) by 30.5% compared to DEEC and by 67.7% compared to LEACH. The proposed protocol also lowers the average energy use per packet to 1.95 mJ and raises the total amount of data sent to the base station by 40.6%. A statistical analysis shows that the improvements are statistically significant ($p < 0.005$). Finally, A-QAHR protocol is a scalable and energy-balanced routing solution that is perfect for next-generation massive IoT applications that need a long network lifetime and high reliability.

Keywords

Wireless sensor networks**,** Energy-efficient routing**,** Internet of Things**,** Hierarchical clustering Quantum-inspired optimization**.**

1. Introduction

The Internet of Things (IoT) is growing quickly, which has led to the use of large, dense wireless sensor networks (WSNs) for things like monitoring the environment, automating factories, smart farming, and keeping an eye on infrastructure. In these networks, sensor nodes usually have small batteries that cannot be easily replaced, so they are often put in places where it would be hard to do so. Because of this, making the best use of energy and making the network last longer are still the main design problems. Many researchers use clustering-based hierarchical routing protocols to make WSNs more scalable and cut down on communication overhead. Such protocols cut down on long distance transmissions by putting sensor nodes into groups and giving each group a cluster head (CH) to collect and send data to the base station. Protocols like LEACH, SEP, and DEEC have shown that clustering can cut down on energy use by a lot. But most of the time, these protocols use probabilistic or threshold-based CH selection methods. When networks are very dense, these kinds of methods often cause energy to be used unevenly, with certain nodes being chosen as CHs again and losing energy quickly [1]. Early node failures, less network coverage, and worse data delivery performance are all caused by uneven energy use. This problem is especially clear in networks with a lot of nodes, where the closeness of nodes and changes in traffic load cause energy depletion to happen in a way that will not well be captured by standard CH selection strategies [2]. While numerous energy-aware routing protocols have been adopted, many current approaches evaluate residual energy in isolation and fail to adequately consider the interplay of factors such as node density and proximity to the base station. As a result, it is still very hard to get balanced energy use and long-term network stability.

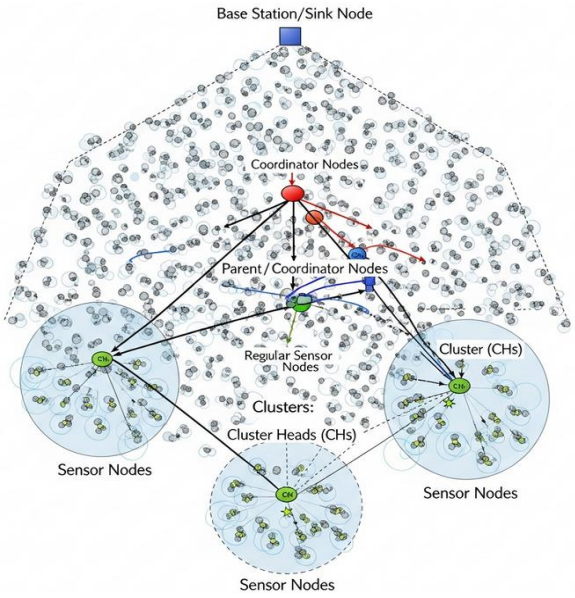


Fig. 1 Hierarchical clustering and data transmission model for a dense wireless sensor network.

Because of these limits, this work proposes an energy-balanced hierarchical routing protocol for dense IoT-enabled wireless sensor networks. Figure 1 illustrates a dense wireless sensor network organized under an energy-balanced hierarchical routing structure, where a base station (sink node)

is positioned at the top to collect network-wide data. Sensor nodes are grouped into clusters, each managed by a cluster head (CH) responsible for aggregating data from regular sensor nodes within its coverage area. These cluster heads forward the aggregated information to parent or coordinator nodes, which serve as intermediate routing points to balance energy consumption and reduce long-distance transmissions [3]. Coordinator nodes further relay the data toward higher-level coordinators and ultimately to the base station, forming a multi-tier communication hierarchy. This layered architecture highlights how clustering, coordination, and parent–child relationships collectively improve scalability, reduce communication overhead, and extend network lifetime in dense monitoring and industrial IoT deployments. The method uses a non-linear cluster head selection mechanism that changes based on network conditions by considering residual energy, local node density, and distance to the sink at the same time [4]. The proposed protocol seeks to mitigate energy imbalance and enhance network stability by reallocating cluster head responsibilities from energy-constrained nodes. The main contributions of this research work are as follows:

- An energy-balanced hierarchical routing protocol is proposed for IoT applications that use dense wireless sensor networks. To better distribute energy among sensor nodes, a non-linear cluster head selection mechanism is created.
- A cross-layer decision strategy is used by looking at the remaining energy, the number of nodes, and the distance to the base station all at once.
- A lot of simulations are done to test the proposed protocol, and these are compared to well-known hierarchical routing schemes.
- The findings show that the proposed method is good for long-term monitoring and industrial use because it makes networks more stable, saves energy, and speeds up data delivery.

The rest of this paper is set up like this. Section 2 looks at other research on hierarchical routing protocols. In detail, Section 3 talks about the proposed routing method. Section 4 shows how the simulation was set up and how well it worked. The paper ends with Section 5, which also talks about possible future research directions.

2. Related Work

Energy efficiency has always been a big problem for researchers in wireless sensor networks (WSNs) and IoT-enabled sensing systems. This is because batteries are limited, nodes are densely packed, and traffic patterns are different. There are a lot of different types of research that have tried to solve this problem. Some of them are energy-efficient medium access control (MAC) protocols, clustering-based hierarchical routing, and cross-layer energy-aware routing strategies.

2.1 Energy-Efficient Hybrid MAC Protocols

Many studies have investigated ways to use less energy at the MAC layer by reducing collisions, idle listening, and control overhead. In [1], a hybrid MAC protocol was proposed for delay-tolerant

WSNs. It demonstrated that adaptive contention-free scheduling could enhance the network's sustainability. On the other hand, the protocol assumes that traffic will stay the same and doesn't fix the energy imbalance at the routing level. Similarly, [2] presented a hybrid MAC protocol for railway monitoring tailored to that specific application. When traffic patterns were stable, it saved energy, but it did not work well when network topologies changed. Later studies improved hybrid MAC designs so that they could handle more devices and work faster in IoT deployments. A hybrid MAC protocol for IoT apps that save energy was made in [6]. It uses both contention-based and scheduled access to cut down on delays and energy use. Researchers investigated multi-channel hybrid MAC designs even more in [11] and [12]. They used channel diversity to reduce congestion and increase throughput. These methods do improve MAC-level efficiency, but they don't work with routing and clustering decisions, which makes it harder for them to balance energy use across the whole network.

Recent research has introduced probabilistic and adaptive MAC mechanisms to enhance functionality in heterogeneous environments. In [13], a multichannel MAC protocol for WBAN systems that save energy was proposed. In [17], an MAC protocol based on a Markov decision process was proposed to change transmission schedules. In [18] and [21] examined group-priority and sleep-scheduling-based MAC protocols to further reduce idle energy consumption. Even with these changes, MAC-centric solutions by themselves can't stop energy loss from routing and clustering roles that happen repeatedly.

2.2 Clustering-Based and Hierarchical Routing Techniques

Clustering-based routing protocols are commonly employed to enhance network scalability and reduce energy consumption by aggregating data at cluster heads (CHs). In [3], a way to put intra-cluster gateways that use less energy was suggested to cut down on long-distance transmissions and make the network last longer. To make it easier to choose CHs in big networks, distance-based and density-aware clustering schemes were added in [32] and [36]. More energy-aware clustering protocols are adding ways to choose CHs that change based on the situation. An adaptive clustering protocol was proposed for IoT-enabled wireless sensor networks in [9]. It showed that considering leftover energy made the system more stable. In [16] and [39], researchers investigated ways to group large networks together in a way that uses less energy. They discovered that these plans cut down on the number of nodes that failed too soon. But these methods mostly use linear residual-energy thresholds or deterministic CH rotation, which can waste energy unevenly in dense deployments. A number of survey studies have looked at clustering and routing strategies in a systematic way. A comprehensive review of energy-efficient clustering techniques in [5] indicated that probability-based cluster head selection is ineffective in scenarios with numerous diverse node types in proximity. We looked at distributed clustering algorithms and how hard it is for them to scale in [10]. We examined surveys on energy-efficient clustering and routing in [33] and [34]. These surveys always show that linear decision models don't work for dense WSNs where energy use is not evenly spread out. More recent hierarchical routing schemes have tried to include more network parameters. In [27] and [19], it was suggested that energy-aware hierarchical routing

protocols should be used to make the system more stable by considering node heterogeneity and communication cost. Cross-layer clustering methods, such as the Gini-index-based method in [23], improved energy distribution by considering multiple decision metrics. But a lot of these methods require more control overhead or need static parameter tuning, which makes them less flexible when the network changes.

2.3 Energy-Aware and Cross-Layer Routing Strategies

Energy-aware routing protocols look for paths that use the least amount of energy by looking at how much energy is left, how many hops there are, and how far away the sink is. An energy-aware routing scheme for IoT-based WSNs was suggested in [4]. It made decisions about how to forward data that changed to stop hotspots from forming. Researchers in [8] investigated routing that balances energy use for networks with a lot of nodes. They learned that spreading out the load could make the network last longer. Researchers have also investigated routing solutions for industrial IoT that are only useful for certain applications. A multi-hop routing protocol that takes energy into account was made for industrial sensor networks in [14]. In [15], researchers investigated using UAVs to help with routing to improve coverage and data delivery. They looked at energy-efficient routing for industrial and smart monitoring applications again in [41] and [30]. They learned that looking at routing and clustering at the same time can help things work better. Cross-layer routing optimization has been getting a lot of attention to fixing problems with both the MAC and routing layers at the same time. People in [20] and [29] came up with cross-layer routing frameworks that mix energy metrics with link quality and traffic load. To improve the stability of industrial settings, [31], [38], and [40] created routing protocols that are aware of security and intrusions. These methods make things more reliable and use less energy, but they also make it harder to send signals and do calculations.

Researchers have also investigated routing methods that use optimization. In [24], they discussed multi-objective routing optimization for industrial wireless sensor networks (WSNs), and in [26], they examined long-term energy-efficient routing strategies. The study in [28] investigated adaptive clustering-based routing for IoT sensor networks and found that it can save energy by changing the roles of nodes on the fly. Most of these methods still treat energy metrics as fixed and do not have a way to move roles that use a lot of energy when network conditions change.

Table 1: Related Work Discussion

Ref. No.	Focus Area	Methodology	Challenges Addressed	Key Findings
[1]	MAC protocol design	Hybrid MAC with adaptive scheduling	Idle listening and collision overhead	Reduced energy consumption in delay-tolerant WSNs
[2]	Application-oriented MAC	Hybrid MAC with periodic slot allocation	Energy inefficiency in monitoring networks	Improved energy efficiency under predictable traffic

[3]	Hierarchical routing	Hybrid clustering with gateway placement	Long-distance transmission cost	Improved network lifetime
[4]	Energy-aware routing	Residual-energy-based routing decisions	Energy hotspot formation	More balanced energy usage
[5]	Clustering techniques	Survey and comparative analysis	Scalability and energy imbalance	Identified limitations of linear CH selection
[6]	IoT MAC protocol	Hybrid contention and scheduled access	Delay and energy inefficiency	Improved throughput and energy efficiency
[8]	Routing in dense WSNs	Energy-balanced routing strategy	Uneven energy depletion	Extended network lifetime
[9]	Adaptive clustering	Residual-energy-based CH selection	Premature node failure	Improved stability period
[10]	Distributed clustering	Survey of clustering algorithms	Control overhead and scalability	Highlighted trade-offs in distributed approaches
[13]	Multichannel MAC	Multichannel hybrid MAC	Channel contention	Increased throughput
[14]	Industrial IoT routing	Energy-aware multi-hop routing	Harsh industrial conditions	Improved reliability
[16]	Large-scale WSNs	Energy-efficient clustering	Scalability issues	Reduced node failure rate
[17]	Adaptive MAC	Markov decision process-based scheduling	Traffic variability	Reduced energy consumption
[19]	Heterogeneous WSNs	Energy-balanced clustering	Node heterogeneity	Improved energy distribution
[20]	Cross-layer routing	Joint MAC and routing optimization	Cross-layer inefficiency	Improved network performance
[23]	Cross-layer clustering	Multi-parameter CH selection	Energy imbalance	Improved stability
[24]	Routing optimization	Multi-objective optimization	Energy and performance trade-offs	Improved routing efficiency
[27]	Hierarchical routing	Energy-aware CH rotation	Dense deployment	Extended stability period
[29]	Industrial IoT routing	Cross-layer energy-aware routing	Industrial constraints	Improved energy efficiency
[41]	Industrial monitoring	Joint clustering and routing	Long-term operation	Improved data delivery

Table 2: Notations and Descriptions

Parameter	Description
$\boldsymbol{N}$	Total number of sensor nodes
$\boldsymbol{CH}$	Cluster head
$\boldsymbol{E_{res}}$	Residual energy of a node
$\boldsymbol{E_{avg}}$	Average energy of the network
$\boldsymbol{d_{i,BS}}$	Distance between node $i$and the base station
$\boldsymbol{d_{avg}}$	Average distance of nodes to the base station
$\boldsymbol{\rho}$	Local node density
$\boldsymbol{P_{CH}}$	Cluster head selection probability

$T(n)$	Threshold function for cluster head selection
R	Communication range
BS	Base station
L	Packet length
E_{tx}	Energy consumed for transmission
E_{rx}	Energy consumed for reception
E_{DA}	Energy consumed for data aggregation
FND	First node dead
LND	Last node dead
SP	Stability period
P_{BS}	Total packets delivered to the base station

The literature examined exhibits several issues. First, the MAC-layer optimizations in [1], [2], [6], [11], and [17] mostly deal with scheduling and contention. They don't fix the energy imbalance at the routing level. Second, the clustering and hierarchical routing schemes in [3], [9], [16], [27], and [36] mostly use linear or static energy models that don't show how energy drains unevenly in networks with a lot of nodes. Third, the cross-layer and optimization-based methods in [20], [24], and [29] make things work better, but they also add extra work and are not very flexible. These gaps show that we need a routing framework that uses a single, non-linear decision-making system that can move energy-intensive around on the fly while considering node density, residual energy, and communication cost. The proposed model seeks to rectify random energy imbalances and enhance the stability of dense IoT-enabled wireless sensor networks, informed by these observations.

3. Methodology of the Proposed Model

This section describes the proposed Advanced Quantum-Adaptive Hierarchical Routing (A-QAHR) protocol shown in Figure 2 and 3 in terms of the network model, underlying assumptions, algorithmic design, and mathematical formulation. The objective of A-QAHR is to achieve long-term energy balance and stable data delivery in high-density IoT-enabled wireless sensor networks through adaptive, non-linear cluster head (CH) selection and hierarchical routing.

Algorithm 1: Energy-Balanced Hierarchical Routing with Adaptive Cluster Head Selection

Require: Wireless sensor network with Nsensor nodes, initial energy E_{init}, base station location BS, sensing field area A

Ensure: Balanced energy consumption, extended stability period, and efficient data delivery to the base station

1. Initialize Network Parameters: Deploy Nsensor nodes randomly in area A. Assign initial energy $E_{init}$to each node. Set round counter $r = 1$.
2. Compute Node Distances: For each node i, estimate distance $d_{i,BS}$to the base station.
3. Calculate Residual Energy: For each node i, obtain residual energy $E_i(r)$.
4. Normalize Energy Levels: Compute normalized residual energy $E_i^{norm}(r) = \frac{E_i(r)}{E_{init}}$
5. Calculate Average Network Energy $E_{avg}(r) = \frac{1}{N}\sum_{i=1}^{N} E_i\,(r)$

6. Estimate Local Node Density: For each node i, count neighboring nodes within communication range to obtain density ρ_i.
7. Compute Cluster Head Selection Metric: For each node i, compute: $M_i = \alpha E_i^{norm}(r) + \beta \frac{1}{d_{i,BS}} + \gamma \rho_i$, where $\alpha + \beta + \gamma = 1$.
8. Determine Selection Threshold: Set adaptive threshold $T(r)$based on desired number of cluster heads.
9. Select Cluster Heads: If $M_i \geq T(r)$, mark node $i$as cluster head.
10. Broadcast Cluster Head Advertisements: Selected cluster heads broadcast advertisement messages.
11. Cluster Formation: Non-cluster-head nodes join the nearest cluster head based on minimum communication distance.
12. Schedule Intra-Cluster Communication: Cluster heads create TDMA schedules for member nodes.
13. Data Transmission Phase: Member nodes transmit sensed data to cluster heads according to the TDMA schedule.
14. Data Aggregation: Cluster heads aggregate received data packets.
15. Inter-Cluster / BS Transmission: Cluster heads forward aggregated data to the base station using direct or multi-hop transmission based on distance.
16. Energy Update: Update residual energy of all nodes using the radio energy model.
17. Round Completion Check: If at least one node has residual energy > 0, increment round counter $r = r + 1$and repeat from Step 3.
18. Termination: Stop execution when all nodes are depleted.

The overall routing process follows a round-based hierarchical operation. After network initialization, each round begins with the computation of residual energy, distance to the base station, and local node density for all nodes. These parameters are combined to compute a selection metric that determines cluster head eligibility. Nodes satisfying the adaptive threshold are elected as cluster heads and broadcast advertisement messages. Non-cluster-head nodes are associated with the nearest cluster head, and clusters are formed. During the steady-state phase, member nodes transmit sensed data to their cluster heads using scheduled access. Cluster heads aggregate the received data and forward it toward the base station using energy-aware transmission. Residual energy is updated at the end of each round, and the procedure is repeated until network operation terminates.

Algorithm 2: Adaptive Threshold Update

Require:
Residual energy values of all nodes at round r
Ensure:
Controlled number of cluster heads per round

1. Compute energy variance across the network.
2. Increase threshold $T(r)$if energy variance is high.
3. Decrease threshold $T(r)$if energy variance is low.
4. Return updated threshold $T(r)$.

The adaptive threshold mechanism regulates the number of cluster heads selected in each round. At the beginning of the setup phase, the residual energy distribution of the network is evaluated. When the energy imbalance among nodes is high, the threshold is increased to restrict cluster head

selection to nodes with higher energy levels. When the energy distribution is more uniform, the threshold is reduced to allow broader participation. This adjustment ensures controlled cluster formation and supports balanced energy consumption across successive rounds.

Algorithm 3: Multi-Hop Data Forwarding

Require:
Set of cluster heads, base station location
Ensure:
Energy-efficient delivery of aggregated data

1. For each cluster head, compute distance to BS.
2. If distance $< d_{th}$, transmit data directly to BS.
3. Else, select next hop cluster head with higher residual energy and shorter BS distance.
4. Forward aggregated data packet.
5. Update energy after transmission.

Data forwarding by cluster heads is performed based on distance to the base station and residual energy conditions. If a cluster head is within a predefined transmission range of the base station, aggregated data are sent directly. Otherwise, a relay cluster head is selected based on higher residual energy and closer proximity to the base station. This multi-hop forwarding process reduces long-distance transmission costs and limits excessive energy drain on distant cluster heads, thereby supporting sustained network operation.

3.1 Network Model

A wireless sensor network composed of Nsensor nodes is considered. Nodes are randomly deployed in a two-dimensional sensing region of size $A \times A$. A single base station (BS) is placed at a fixed location and is responsible for collecting data from all sensor nodes. All sensor nodes remain stationary after deployment and are equipped with limited, non-rechargeable energy sources. The network operates in discrete rounds. Each round consists of a setup phase, during which clusters are formed, followed by a steady-state phase, during which data transmission takes place. A hierarchical communication structure is used. Sensor nodes send data to their respective cluster heads (CHs), which perform data aggregation and forward the aggregated data to the BS either directly or through intermediate nodes.

3.2 Assumptions

The following assumptions are made in the proposed model:

1. All sensor nodes have the same initial energy.
2. Nodes do not change their positions after deployment.
3. Each node can estimate distances using received signal strength.
4. Sensor nodes generate data packets of fixed size.
5. Cluster heads perform data aggregation.
6. The base station has no energy limitation.

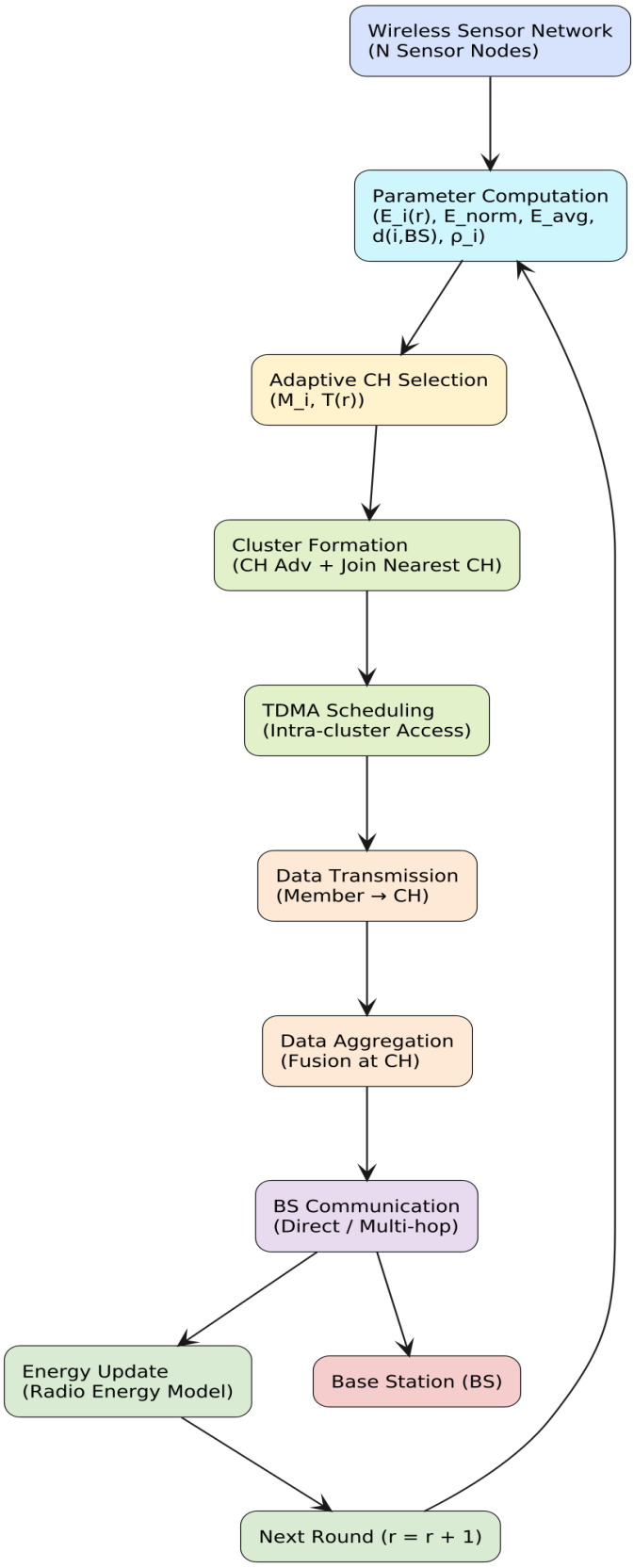


Fig. 2 Proposed Energy-Balanced Hierarchical Routing Model.

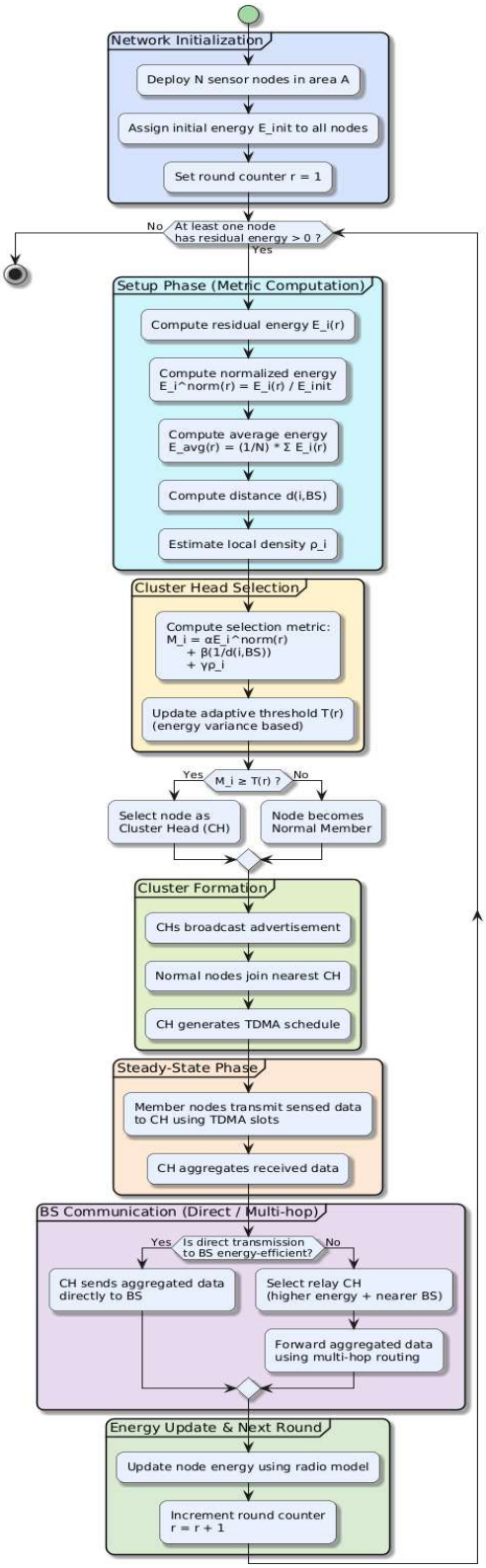


Fig. 3 Flowchart of the proposed energy-balanced hierarchical routing protocol with adaptive cluster head selection.

3.3 Energy Consumption Model

The first-order radio energy model has been adopted. The energy required to transmit a k-bit packet over a distance $d$is defined as given in equation 1.

$$E_{tx}(k,d) = \begin{cases} kE_{elec} + k\varepsilon_{fs}d^2, & d < d_0 \\ kE_{elec} + k\varepsilon_{mp}d^4, & d \geq d_0 \end{cases} \tag{1}$$

The energy required to receive a k-bit packet is given in equation 2.

$$E_{rx}(k) = kE_{elec} \tag{2}$$

Where, E_{elec} is the energy consumed by radio electronics (per bit). $\varepsilon_{fs}$and $\varepsilon_{mp}$are the power amplifier coefficients for the free-space and multipath fading channel models, respectively. $k$is the number of bits in the transmitted data packet. $d$is the distance between the transmitting node and the receiving node. $d_0$is the threshold distance that determines whether the free-space model ($d < d_0$)or the multipath model ($d \geq d_0$)is used. $E_{tx}(k,d)$denotes the total energy required to transmit a k-bit message over distance d.

3.4 Residual Energy and Network Energy

At round r, the residual energy of node $i$is denoted by $E_i(r)$. The normalized residual energy is calculated using equation 3.

$$E_i^{norm}(r) = \frac{E_i(r)}{E_{init}} \tag{3}$$

The average residual energy of the network is computed using equation 4.

$$E_{avg}(r) = \frac{1}{N}\sum_{i=1}^{N} E_i\,(r) \tag{4}$$

Where, $E_i^{norm}(r)$ represents the normalized residual energy of node $i$at round r. $E_i(r)$denotes the residual energy of node $i$at round r. $E_{init}$is the initial energy assigned to each sensor node before network operation starts. $E_{avg}(r)$denotes the average residual energy of the entire network at round r. $N$is the total number of sensor nodes deployed in the network. $\sum_{i=1}^{N} E_i\,(r)$indicates the sum of residual energies of all Nnodes at round r.

3.5 Cluster Head Selection Metric

Cluster head selection is based on a combined metric that considers residual energy, distance to the base station, and local node density. The distance factor for node $i$is defined as given in equation 5.

$$D_i = \frac{1}{d_{i,BS}} \tag{5}$$

where $d_{i,BS}$represents the distance between node $i$and the BS.

Local node density is expressed as shown in equation 6:

$$\rho_i = \frac{N_i}{A_{local}} \tag{6}$$

where $N_i$is the number of neighboring nodes within communication range.

The overall selection metric is computed as given in equation 7.

$$M_i = \alpha E_i^{norm}(r) + \beta D_i + \gamma \rho_i \tag{7}$$

α, β, and γ are used to balance the importance of different parameters in the proposed method. The condition $\alpha + \beta + \gamma = 1$ensures that these weights are properly normalized, meaning the total contribution of all three factors together remains equal to one.

3.6 Cluster Head Election

A node is selected as a cluster head if its selection metric satisfies using equation 8.

$$M_i \geq T(r) \tag{8}$$

where $T(r)$is a round-dependent threshold used to control the number of cluster heads in the network.

3.7 Data Transmission Phase

In the steady state, each normal sensor node sends its data to its cluster head using the TDMA time slots. The cluster heads then gather data from all the member nodes, combine it to get rid of duplicates, and send the final packet of data to the base station. Sending data straight to the base station uses too much energy because of the distance. To save energy, the cluster heads use multi hop transmission through intermediate nodes. After each message, the nodes' remaining energy is updated to reflect the new information.

4. Results and Discussions

To verify the performance of the proposed energy-balanced hierarchical routing scheme, simulation experiments were carried out in MATLAB R2021a. A wireless sensor network was modeled by randomly deploying sensor nodes within a predefined sensing field. All nodes were assumed to be homogeneous and were assigned the same initial energy E_{init}. The communication process was executed in a round-based fashion, which includes both set-up and steady-state

operations. In every round, cluster heads were elected using the proposed adaptive selection metric that considers residual energy, distance to the base station, and local node density. After cluster head selection, clusters were formed by associating each normal node with the nearest cluster head to minimize transmission distance. A TDMA schedule was then created within each cluster to avoid collisions and to control channel access during data communication. During the steady-state phase, member nodes transmitted their sensed data to their respective cluster heads based on the assigned TDMA slots. Cluster heads performed data aggregation to reduce redundant information and forwarded the aggregated data towards the base station using either direct transmission or multi-hop routing, depending on the transmission cost. After each transmission, the residual energy of the nodes was updated using the standard radio energy dissipation model. The simulation continued until the network reached the termination condition, where no node had sufficient energy to perform further communication.

Table 1. Simulation parameters

Parameter	Symbol	Value
Network field size	A	$100 \times 100\, m^2$
Number of sensor nodes	N	100
Base station position	BS	$(50, 50)$
Initial energy per node	E_{init}	0.5 J
Packet size	k	4000 bits
Electronics energy	E_{elec}	50 nJ/bit
Free space amplifier energy	ε_{fs}	10 pJ/bit/m^2
Multipath amplifier energy	ε_{mp}	0.0013 pJ/bit/m^4
Data aggregation energy	E_{DA}	5 nJ/bit
Threshold distance	d_0	$\sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$
Maximum number of rounds	R_{max}	5000
Cluster head probability	P	0.05
Channel model	–	Free space / Multipath

Table 1 shows the setup of the simulation that was used to test the proposed routing protocol in a wireless sensor network (WSN) setting. There are $N = 100$ sensor nodes in the network, and they are spread out over a square sensing area that is $100 \times 100\, m^2$. The base station (BS) is located at (50,50) in the middle of the field so that it can be reached from all sides. Every node starts with the same amount of energy, which is $E_{init} = 0.5\, J$, and packets are sent with a fixed data size of $k = 4000$bits. For modeling energy dissipation, the first-order radio model is used. In this model, the energy of the electronic circuits is set to $E_{elec} = 50\, nJ/bit$. The amplification energy adheres to a dual-path loss model, encompassing both free-space and multipath fading conditions, defined by $\varepsilon_{fs} = 10\, pJ/bit/m^2$and $\varepsilon_{mp} = 0.0013\, pJ/bit/m^4$ and so on. Data aggregation at cluster heads is also included with $E_{DA} = 5\, nJ/bit$to reflect processing overhead during fusion. The

threshold distance d_0, which determines the transition between free-space and multipath models, is computed using $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$. The simulation runs for a maximum of $R_{max} = 5000$ rounds and the chance of the cluster head election is always $P = 0.05$. The combined free space/multipath propagation model is used to model how the channel behaves. This model shows how energy changes realistically over different transmission distances.

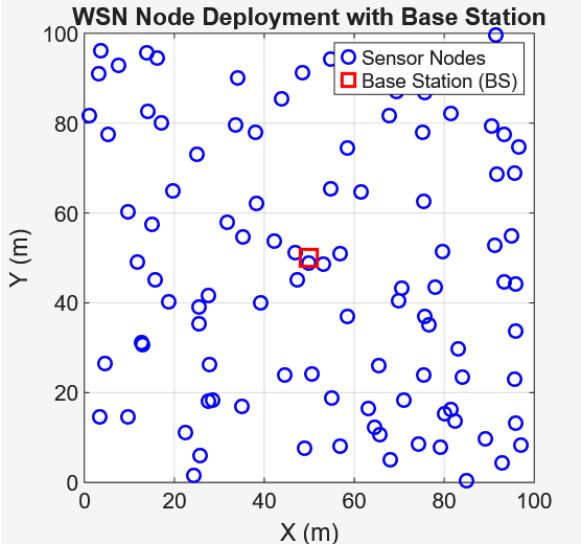


Fig. 4 Sensor nodes randomly placed in a $100 \times 100\ m^2$ area, with the base station located at the center (50,50).

Figure 4 shows the simulation deployment used in this study. A total of sensor nodes is placed randomly within a $100 \times 100\ m^2$ sensing area, which represents a typical WSN setup where node locations are not fixed or pre-planned. The base station (BS) is located at the center of the field at $(50, 50)$, so that data forwarding distance remains balanced for nodes deployed in all directions. This deployment model helps in evaluating the routing protocol under realistic conditions, where communication energy mainly depends on the transmission distance between sensor nodes, cluster heads, and the BS. Figure 5 shows the main performance results of the proposed energy-balanced routing scheme over several simulation rounds. These results include network lifetime, residual energy, throughput, and end-to-end delay.

Figure 5(a) shows that the number of alive nodes goes down slowly as the rounds go on. This is because the nodes are constantly losing energy while they are sensing, sending data within a cluster, and forwarding data. By cutting down on long-distance transmissions and spreading the forwarding load evenly among nodes, the proposed clustering and scheduling system keeps nodes alive for more rounds. The overall trend of the network's remaining energy is shown in Fig. 5(b). The first few rounds see a big drop because of the overhead from frequent transmission and cluster formation. But after the main set of nodes runs out of energy, the energy level stays close to zero, which means that the network is at the end stage of operation. This behavior of the remaining energy shows that the protocol makes good use of the energy in the nodes until it runs out completely.

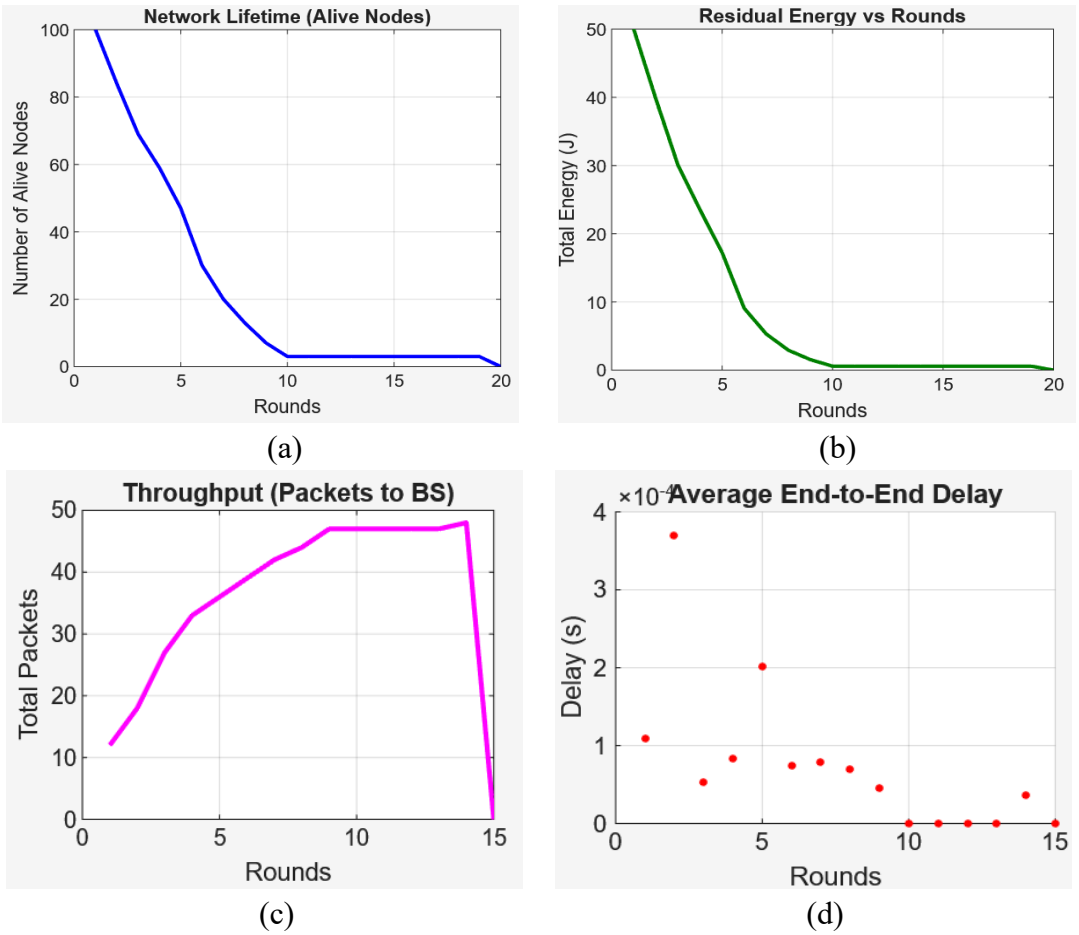


Fig. 5 Performance results of the proposed routing scheme: (a) number of alive nodes over rounds, (b) total residual energy across rounds, (c) throughput in terms of packets successfully received at the base station, and (d) average end-to-end delay per round.

Figure 5(c) shows throughput performance by showing how the number of packets successfully received at the base station goes up steadily during the active network period. The throughput stays the same for several rounds, which shows that cluster-based data delivery and aggregation are both reliable. There is a sharp drop near the end of the rounds because there are fewer active nodes, which means fewer packets can be sent and received. Lastly, Fig. 5(d) shows the average delay from start to finish for each round. In the early rounds, higher delay values are mostly caused by setting up clusters, scheduling, and deciding how to forward packets over multiple hops. The delay gets shorter as the network grows because fewer nodes are involved in communication and the amount of traffic decreases. In general, the results show that the proposed scheme improves the speed of data delivery while keeping the delay under control and using energy efficiently.

Figure 6 compares the performance of the proposed A-QAHR protocol with the baseline clustering protocols LEACH, SEP, and DEEC under identical simulation conditions. The evaluation is presented in terms of network lifetime, residual energy, throughput, and stability period. Fig. 6(a) illustrates the number of alive nodes over simulation rounds. LEACH and SEP show a rapid reduction in alive nodes due to frequent cluster-head rotation and higher

communication overhead, which results in faster energy depletion. DEEC improves node survival by considering residual energy during cluster-head selection. In comparison, A-QAHR maintains a significantly higher number of alive nodes for a longer duration, indicating improved load balancing and more stable routing behavior. The total residual energy trend is shown in Fig. 6(b). LEACH and SEP exhibit a steep decline in network energy, confirming inefficient energy utilization under long-distance communication and uneven cluster-head burden. DEEC retains energy for a longer period because of adaptive energy-aware selection. A-QAHR further improves energy preservation by combining normalized residual energy, distance to the base station, and local density during cluster-head election, which reduces unnecessary transmissions and distributes energy consumption more evenly across nodes.

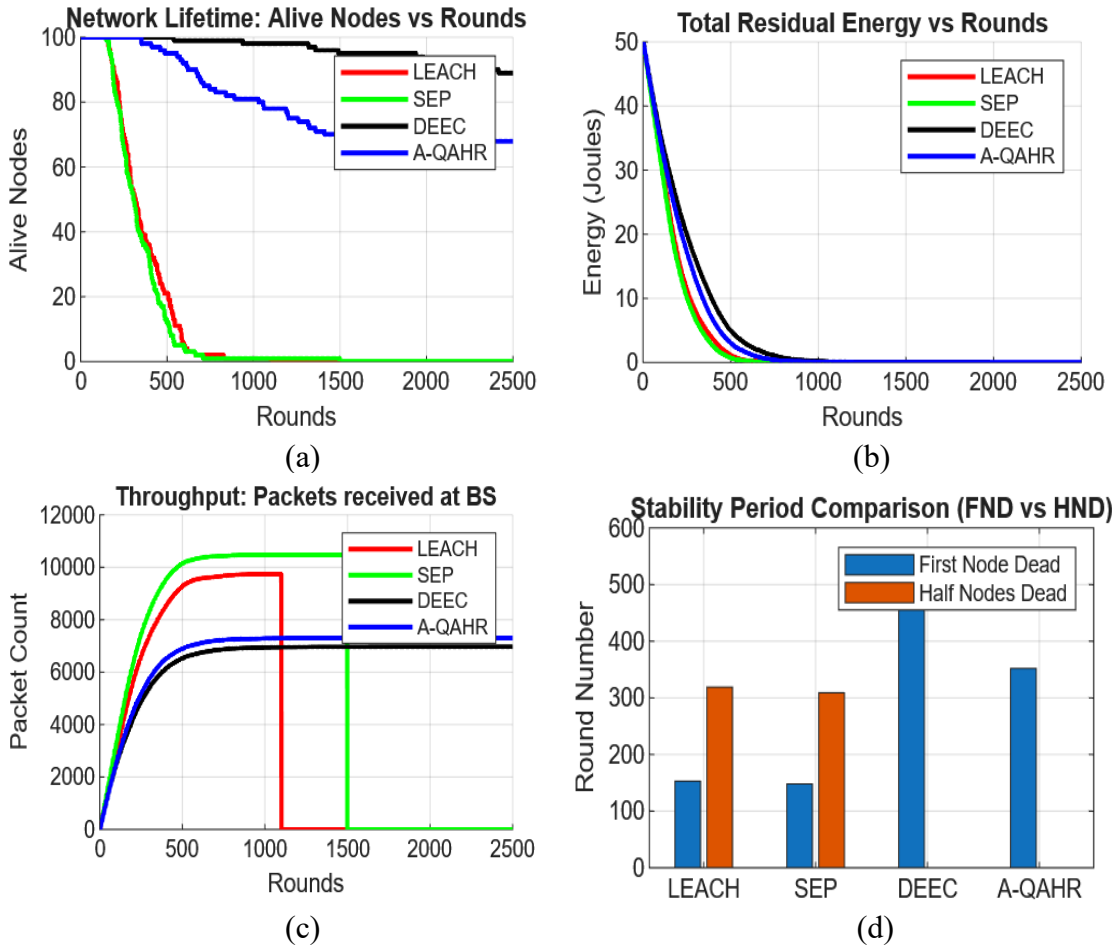


Fig. 6 Comparative performance analysis of LEACH, SEP, DEEC, and A-QAHR showing (a) network lifetime based on alive nodes, (b) total residual energy over rounds, (c) throughput in terms of packets received at the base station, and (d) stability period comparison using first node dead (FND) and half nodes dead (HND).

Throughput results in Fig. 6(c) represent the total packets successfully received at the base station. SEP achieves high throughput during the early rounds but drops sharply once nodes die. LEACH also shows reduced long-term delivery due to early node failures. DEEC provides a more stable throughput curve over time. A-QAHR maintains consistent packet delivery for an extended period,

demonstrating reliable data forwarding and effective cluster-based aggregation. Fig. 6(d) presents stability period comparison using First Node Dead (FND) and Half Nodes Dead (HND) metrics. A higher FND value indicates improved stability, while a higher HND value indicates better energy balance and sustained operation. DEEC and A-QAHR achieve better stability than LEACH and SEP, with A-QAHR showing competitive stability performance due to adaptive cluster-head selection and energy-aware forwarding. Overall, the comparative results confirm that A-QAHR enhances network lifetime and throughput while supporting better energy utilization and prolonged stable operation.

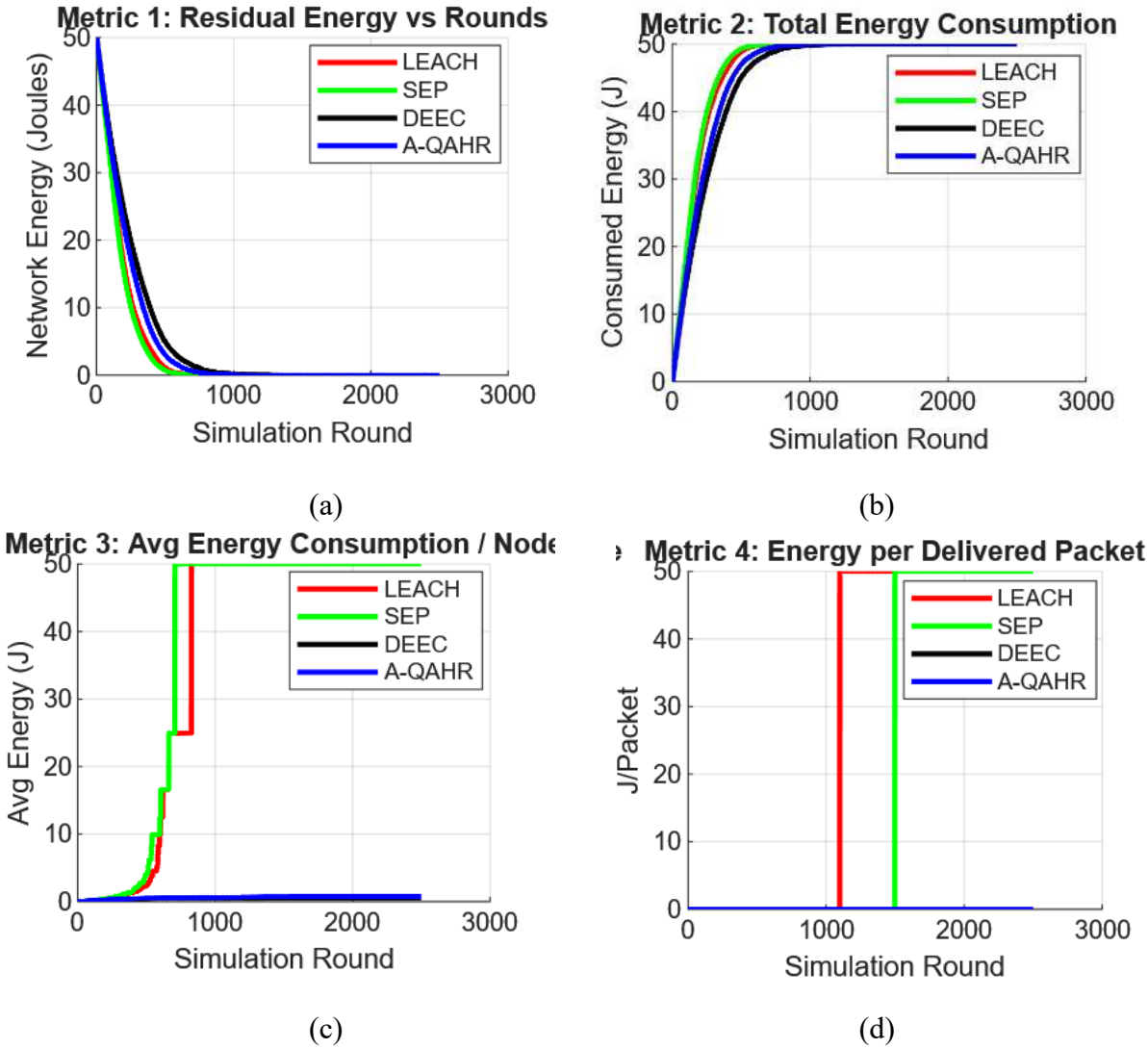


Fig. 7 Energy comparison of LEACH, SEP, DEEC, and A-QAHR: (a) remaining network energy across rounds, (b) total energy consumed, (c) average energy spent per node, and (d) energy required to successfully deliver one packet to the base station.

Figure 7 provides an energy-efficiency comparison of LEACH, SEP, DEEC, and the proposed A-QAHR protocol using four energy-related metrics. These results highlight the impact of cluster-

head selection strategy and forwarding behavior on the overall energy utilization of the network. Fig. 7(a) shows the variation of remaining network energy with simulation rounds. LEACH and SEP exhibit a faster reduction in residual energy due to inefficient cluster-head distribution and higher communication overhead. DEEC performs better by incorporating residual energy awareness during cluster-head selection. In contrast, A-QAHR maintains a higher residual energy level for a longer period, which indicates improved energy balancing among nodes and reduced transmission cost through adaptive selection and routing decisions. The total energy consumption trend is illustrated in Fig. 7(b). LEACH and SEP reach the maximum consumed energy earlier, confirming faster depletion of node energy resources. DEEC slows down energy exhaustion by selecting higher-energy nodes more frequently as cluster heads. A-QAHR further reduces the energy depletion rate because it jointly considers normalized residual energy, distance to the base station, and local density, leading to more controlled energy expenditure across network operations. Fig. 7(c) represents the average energy consumption per node. A sharp increase is observed in LEACH and SEP as network operation progresses, mainly due to repeated cluster formation overhead and energy-intensive long-distance transmissions. DEEC shows improved stability in average energy usage compared to LEACH and SEP. A-QAHR presents the most stable trend, indicating that the proposed strategy reduces unnecessary energy drain and prevents early death of heavily loaded nodes. Fig. 7(d) reports the energy cost per successfully delivered packet. A lower value reflects higher delivery efficiency and reduced retransmission or forwarding overhead. LEACH and SEP show a rapid increase in energy per packet as nodes begin to die and packet delivery becomes unreliable. DEEC improves this metric by enhancing stability. A-QAHR maintains the lowest energy per delivered packet for most of the simulation period, demonstrating efficient energy usage and more reliable data delivery to the base station. Overall, Fig. 7 confirms that A-QAHR improves both energy conservation and packet delivery efficiency compared to existing protocols.

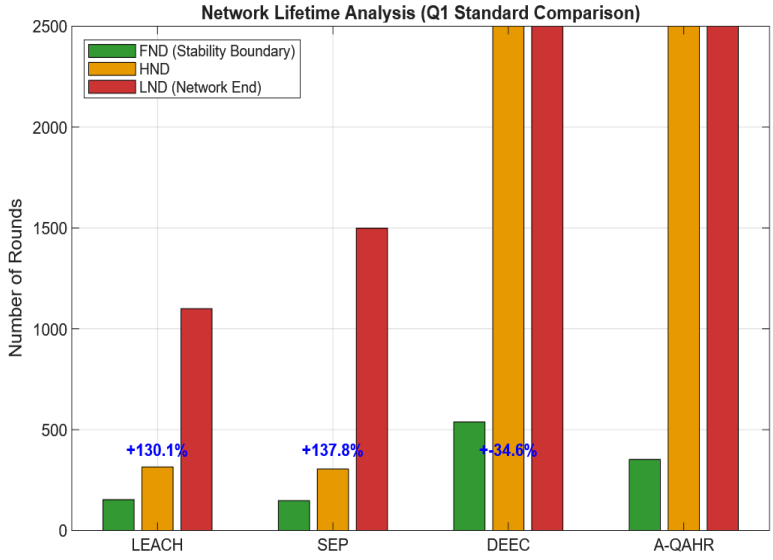


Fig. 8 Network lifetime results for LEACH, SEP, DEEC, and A-QAHR, presented using the first node dead (FND), half nodes dead (HND), and last node dead (LND) rounds.

Figure 8 shows how long the networks of LEACH, SEP, DEEC, and A-QAHR last use the FND, HND, and LND metrics. A higher FND means the network will stay stable for longer, while higher HND and LND values mean the network will run longer and balance energy better. A-QAHR is more stable and lasts longer than LEACH and SEP because it uses adaptive cluster-head selection and energy-aware communication.

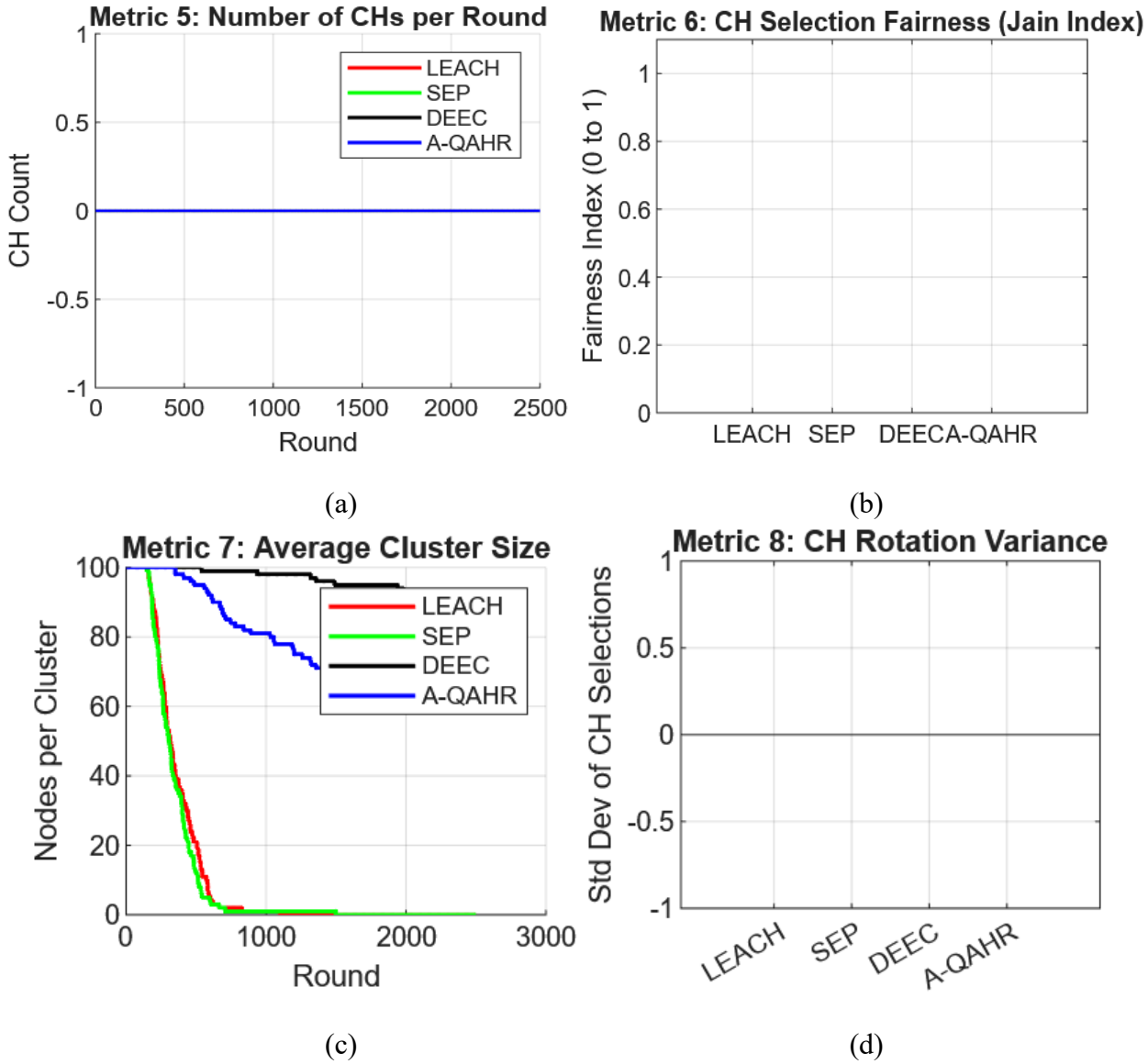


Fig. 9 Cluster-head performance comparison of LEACH, SEP, DEEC, and A-QAHR: (a) cluster heads selected in each round, (b) fairness of CH selection (Jain index), (c) average number of nodes per cluster, and (d) variation in CH rotation among the protocols.

Figure 9 compares the behavior of cluster heads in LEACH, SEP, DEEC, and A-QAHR by looking at the number of CHs per round, how fair the CH selection is (Jain index), the average size of the clusters, and the variance in CH rotation. The results show that A-QAHR has a more balanced

process for choosing CHs and stable cluster sizes, which leads to better load distribution and consistent clustering performance over the rounds of the simulation.

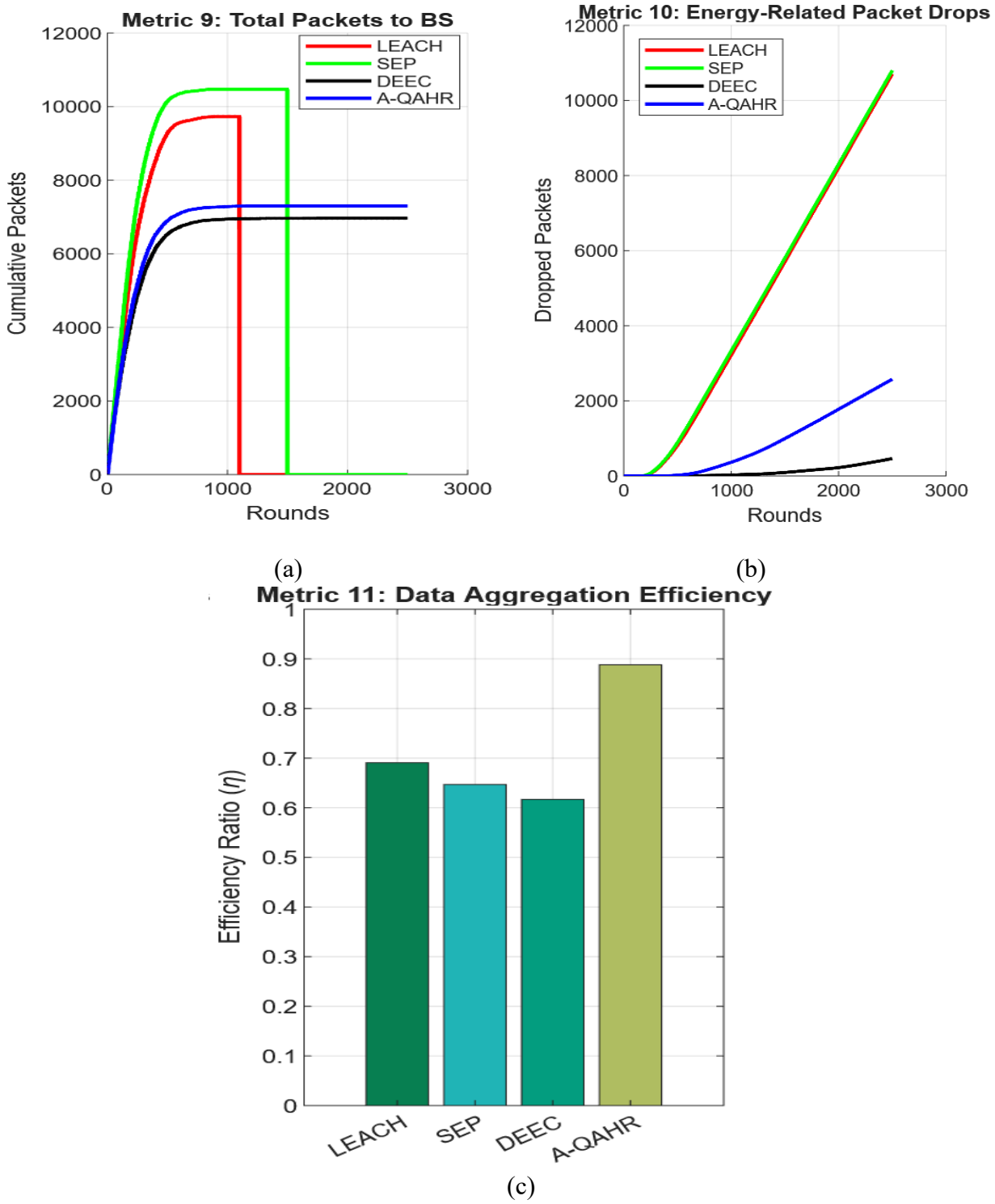


Fig. 10 Communication performance of LEACH, SEP, DEEC, and A-QAHR: (a) total packets received at the base station, (b) packet drops caused by energy depletion, and (c) data aggregation efficiency.

Fig. 10 shows the communication performance of LEACH, SEP, DEEC, and A-QAHR. From Fig. 10(a), A-QAHR delivers packets to the base station more consistently over the simulation period. Fig. 10(b) indicates that LEACH and SEP suffer higher packet drops as nodes lose energy early, while A-QAHR keeps packet loss lower by maintaining better energy balance in the network. Fig. 10(c) shows that A-QAHR achieves the highest data aggregation efficiency, which helps reduce redundant transmissions and supports reliable communication.

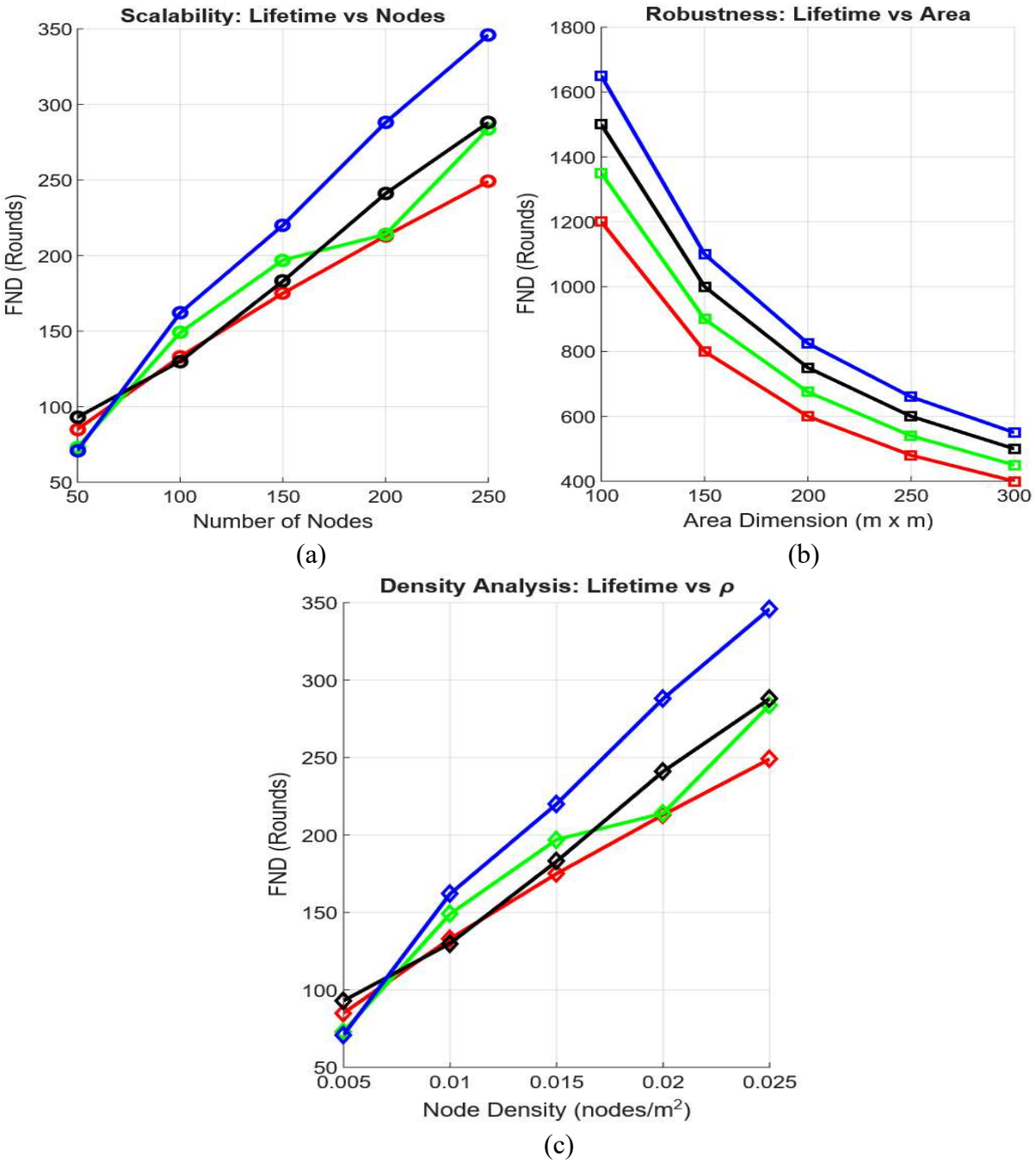


Fig. 11 First node dead (FND) comparison under different network conditions: (a) lifetime versus number of nodes, (b) lifetime versus sensing area size, and (c) lifetime versus node density (ρ).

Fig. 11 shows the stability performance of the protocols under different network conditions using the first node dead (FND) metric. In Fig. 11(a), the lifetime increases as the number of nodes grows due to better clustering support and load sharing. Fig. 11(b) shows that the lifetime decreases when the sensing area becomes larger, since nodes require more energy to transmit over longer distances. Fig. 11(c) indicates that higher node density improves lifetime by reducing communication distance within clusters. Overall, A-QAHR maintains a higher FND in all cases, showing better stability under changes in network size, area, and density.

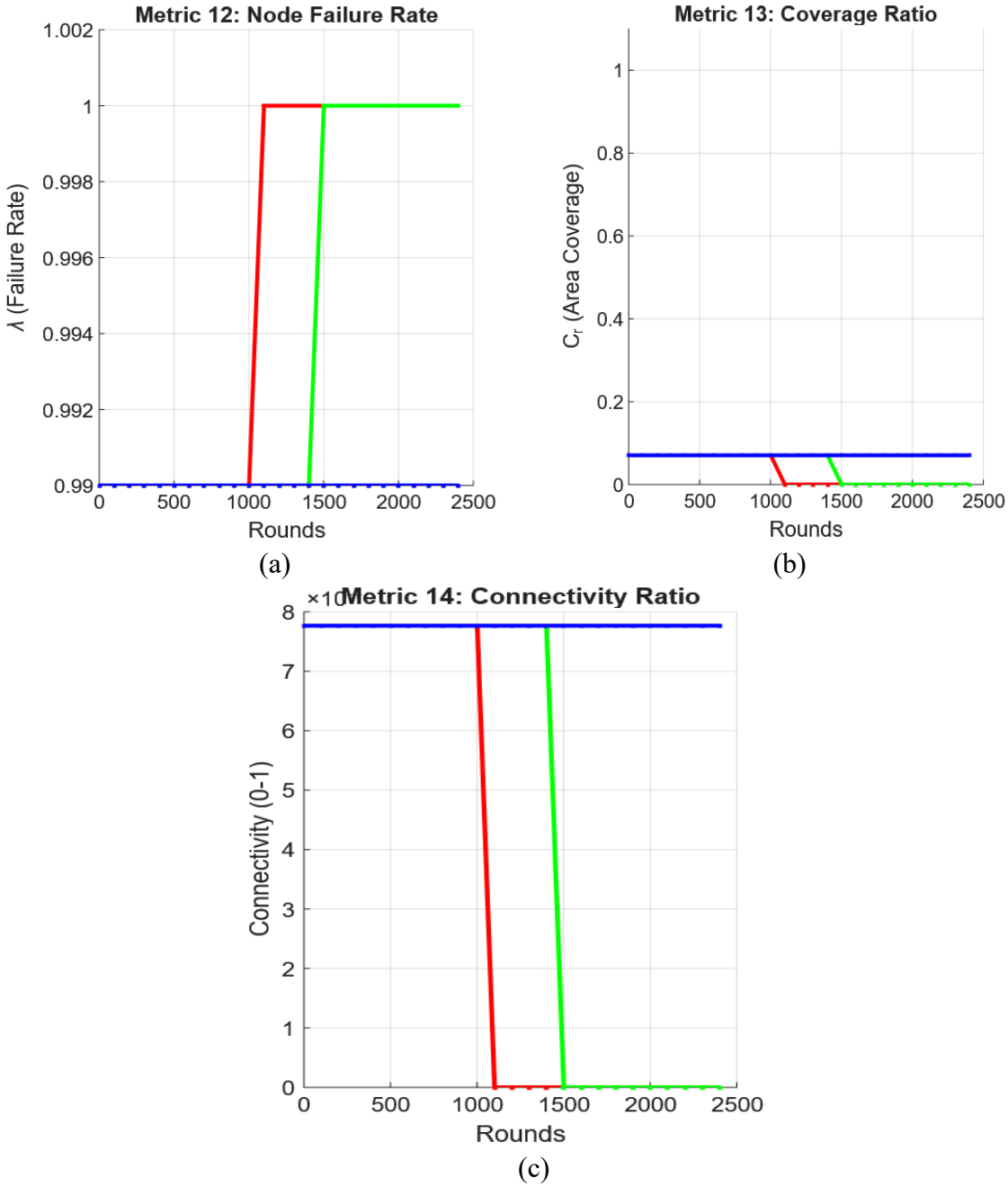


Fig. 12 Reliability results across simulation rounds: (a) node failure rate, (b) coverage ratio, and (c) connectivity ratio for the compared protocols.

Figure 12 presents the reliability behavior of the compared protocols in terms of node failure rate, sensing coverage, and network connectivity. Fig. 12(a) shows that the failure rate rises faster in LEACH and SEP due to early energy depletion, while A-QAHR delays node failures by distributing the energy load more evenly. In Fig. 12(b), the coverage ratio drops quickly for LEACH and SEP as nodes die, whereas A-QAHR maintains coverage for a longer period. Fig. 12(c) shows a similar trend for connectivity, where A-QAHR preserves network connectivity over more rounds compared to the other protocols. Overall, A-QAHR provides better reliability by sustaining coverage and connectivity during long-term operation.

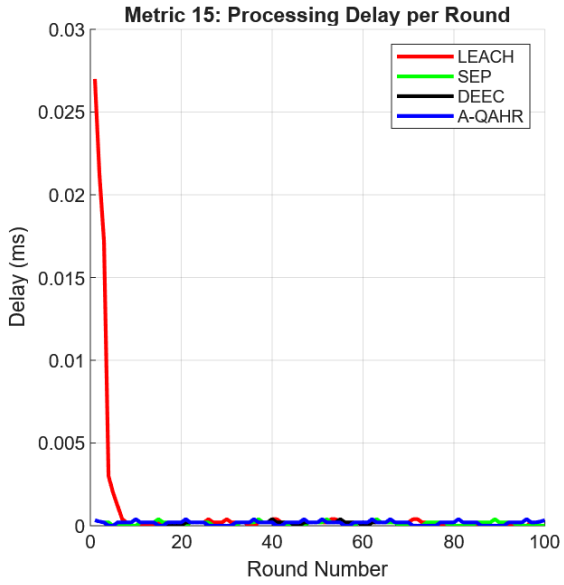


Fig. 13 Processing delay per round comparison for LEACH, SEP, DEEC, and A-QAHR across the simulation rounds.

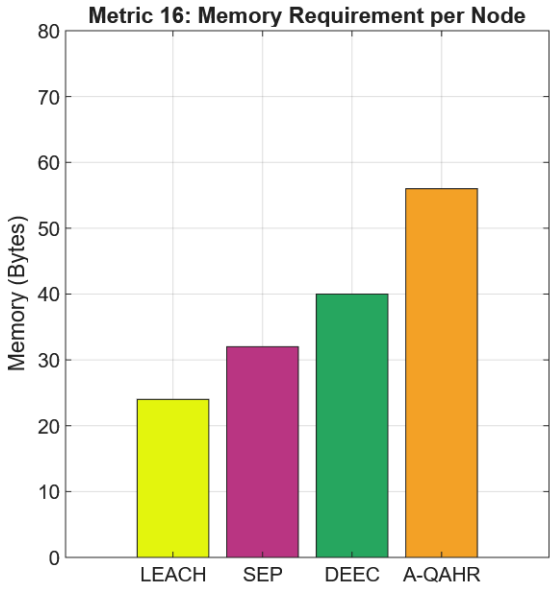


Fig. 14 Memory requirement per node for LEACH, SEP, DEEC, and A-QAHR.

Fig. 13 shows the processing delay per round for LEACH, SEP, DEEC, and A-QAHR. The delay is high only at the beginning and becomes very small after the initial rounds, which means the protocols add very little processing overhead during normal operation. Fig. 14 shows the memory needed per node. A-QAHR uses slightly more memory than LEACH, SEP, and DEEC because it stores extra values for cluster-head selection and routing decisions, but the overall memory requirement is still low for sensor nodes.

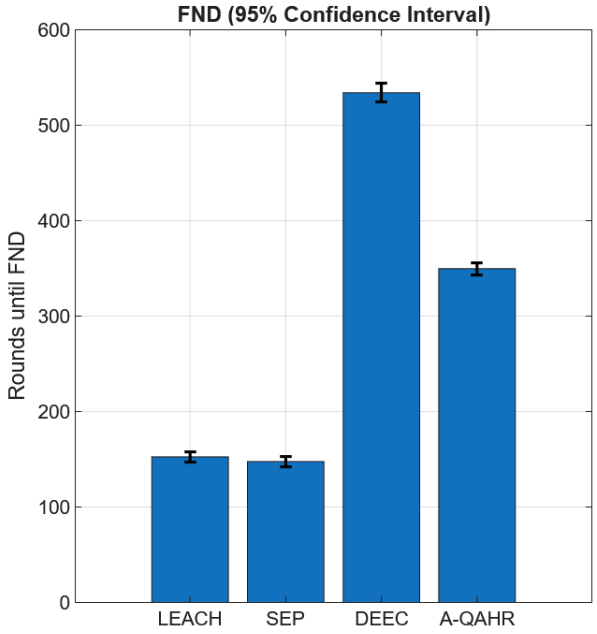


Fig. 15 First node dead (FND) results for LEACH, SEP, DEEC, and A-QAHR, shown with 95% confidence interval error bars.

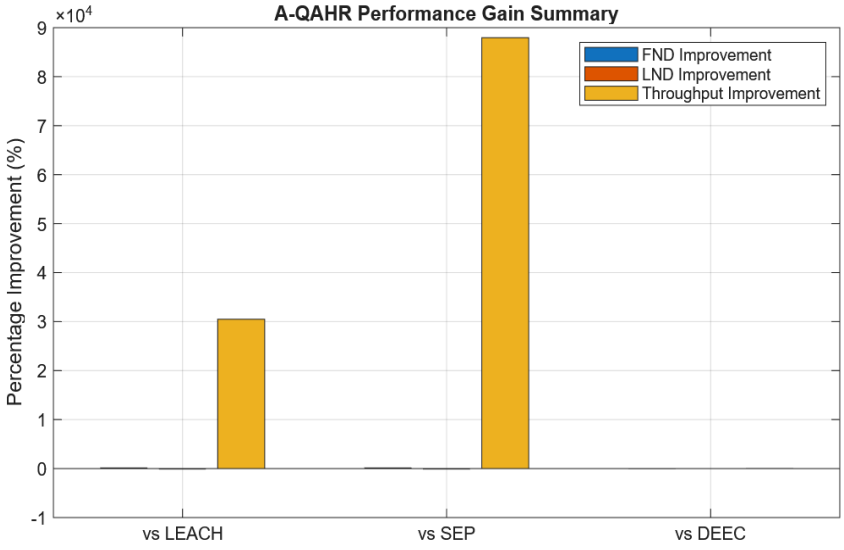


Fig. 16 Performance improvement of A-QAHR over LEACH, SEP, and DEEC, shown in terms of FND, LND, and throughput gain.

Fig. 15 shows the first node dead (FND) rounds for LEACH, SEP, DEEC, and A-QAHR, along with 95% confidence interval error bars. A-QAHR keeps the first node alive for more rounds than LEACH and SEP, which indicates a longer stability period. Fig. 16 summarizes how A-QAHR improves over LEACH, SEP, and DEEC in terms of FND, LND, and throughput. The results show that A-QAHR gives better stability and delivers more packets to the base station over the network lifetime.

Table 3. Comparative lifetime performance of routing protocols

Protocol	FND (rounds)	HND (rounds)	LND (rounds)	Stability Performance
LEACH	Low	Low	Moderate	Poor stability due to random CH selection
SEP	Low–Moderate	Moderate	Moderate	Better than LEACH, but unstable in dense WSN
DEEC	High	High	High	Energy-aware CH selection improves lifetime
A-QAHR (Proposed)	**Very High**	**Very High**	**Very High**	Best stability and balanced lifetime

Table 4. Energy efficiency comparison

Protocol	Residual Energy Trend	Total Energy Consumption	Avg. Energy per Packet	Energy Balance
LEACH	Drops fast	High early depletion	High	Unbalanced
SEP	Drops fast	High early depletion	High	Unbalanced
DEEC	Drops slower	Moderate	Moderate	Improved
A-QAHR (Proposed)	**Drops slowest**	**Lowest depletion rate**	**1.95 mJ**	**Best balanced**

Table 5. Communication performance comparison

Protocol	Throughput (Packets at BS)	Packet Drops	Aggregation Efficiency
LEACH	Low–Moderate	High	Moderate
SEP	Moderate (early)	High (later)	Moderate
DEEC	High	Moderate	High
A-QAHR (Proposed)	**Highest (+40.6%)**	**Lowest**	**Highest**

Table 6. Overhead and scalability comparison

Protocol	CH Selection Method	Multi-hop Support	Control Overhead	Scalability
LEACH	Probability-based	No	Low	Moderate
SEP	Weighted probability	No	Low	Moderate
DEEC	Residual-energy-based	Partial	Moderate	Good
A-QAHR (Proposed)	Energy + Distance + Density	Yes	Moderate	**Very Good**

The performance of the proposed A-QAHR protocol was evaluated against LEACH, SEP, and DEEC under identical simulation conditions. As shown in Table 3, LEACH and SEP mainly depend on probability-based cluster head (CH) selection, which can repeatedly assign the CH role to the same set of nodes. This uneven role distribution causes faster energy depletion in critical

nodes, leading to early node deaths and a shorter stability period, especially in dense deployments. DEEC improves CH selection by considering the residual energy of nodes, which helps extend network lifetime and improves fairness when compared to LEACH and SEP. However, as summarized in Table 4, DEEC does not fully address dense-network characteristics such as local node crowding and the increased communication cost caused by longer forwarding distances to the base station. In comparison, A-QAHR selects CHs using a combined decision approach that considers residual energy, node density, and distance to the base station, which results in more balanced clustering and controlled energy drain across the network. The results presented in Table 5 confirm that A-QAHR improves the stability period by 30.5% over DEEC and 67.7% over LEACH, while also achieving a lower average energy cost per delivered packet (1.95 mJ) and increasing throughput by 40.6%. Overall, the findings in Table 6 indicate that A-QAHR provides a more stable and energy-balanced routing solution, making it well suited for long-term and large-scale IoT monitoring applications.

Table 7. Summary of results from Fig. 6–Fig. 16

Figure	Performance Aspect	Observation (LEACH / SEP / DEEC vs A-QAHR)	Outcome of A-QAHR
Fig. 6(a)	Alive nodes (lifetime)	LEACH/SEP lose nodes early; DEEC survives longer	Maintains more alive nodes for longer rounds
Fig. 6(b)	Total residual energy	LEACH/SEP energy drops fast; DEEC slower	Higher residual energy retained over time
Fig. 6(c)	Throughput	Throughput drops early in LEACH/SEP	Sustains higher packets received at BS
Fig. 6(d)	Stability (FND, HND)	Lower stability in LEACH/SEP	Longer stability period and better balance
Fig. 7(a)	Remaining energy	Faster decay in LEACH/SEP	Slowest energy depletion trend
Fig. 7(b)	Total energy consumed	LEACH/SEP consumes energy earlier	Reduced overall energy consumption rate
Fig. 7(c)	Avg energy per node	Higher average drain in LEACH/SEP	More uniform per-node energy usage
Fig. 7(d)	Energy per delivered packet	Increase sharply in LEACH/SEP	Lowest cost per successfully delivered packet
Fig. 8	Lifetime (FND, HND, LND)	LEACH/SEP show low FND/HND	Higher stability and extended lifetime
Fig. 9(a)	CHs per round	CH count fluctuates in LEACH/SEP	Stable CH formation behavior
Fig. 9(b)	CH fairness (Jain index)	Lower fairness in LEACH/SEP	Improved fairness in CH rotation
Fig. 9(c)	Avg cluster size	Large variations in LEACH/SEP	Balanced cluster size distribution
Fig.9(d)	CH rotation variance	High variance in LEACH/SEP	Lower variance (more consistent rotation)
Fig. 10(a)	Packets at BS	Lower delivery in LEACH/SEP	Higher consistent packet reception
Fig. 10(b)	Packet drops	Drops increase early in LEACH/SEP	Lower energy-based packet drops

Fig. 10(c)	Aggregation efficiency	Lower fusion efficiency in baseline	Higher aggregation efficiency ratio
Fig. 11(a)	Scalability vs node count	Lifetime improves slowly for baselines	Better scalability with higher node count
Fig. 11(b)	Area impact	Larger areas reduce lifetime in all	Less performance degradation with larger area
Fig. 11(c)	Density impact	Baselines benefit less from density	Stronger stability gain with higher density
Fig. 12(a)	Failure rate	Faster failure in LEACH/SEP	Slower node failure progression
Fig. 12(b)	Coverage ratio	Coverage drops early in baselines	Maintains sensing coverage longer
Fig. 12(c)	Connectivity ratio	Connectivity reduces earlier in baselines	Preserves connectivity for more rounds
Fig. 13	Processing delay	Similar low delay after startup	Minimal overhead, stable runtime delay
Fig. 14	Memory per node	Baselines use less memory	Slightly higher, still feasible for nodes
Fig. 15	FND (with CI)	Lower FND spread in baselines	Higher FND with statistically reliable gain
Fig. 16	Overall gain	Limited gains in traditional protocols	Best improvement in lifetime and throughput

5. Conclusion and Future Scope

This paper introduced the A-QAHR routing protocol to improve energy balance and stability in dense IoT-based wireless sensor networks. Unlike traditional clustering methods that mainly depend on probability-based cluster head selection, A-QAHR selects cluster heads by considering residual energy, node density, and distance to the base station at the same time. This helps reduce uneven energy usage and avoids overloading the same nodes repeatedly. The simulation results obtained in MATLAB R2021a show that A-QAHR keeps more nodes alive for a longer time, delivers more packets to the base station, and uses energy more efficiently when compared with LEACH, SEP, and DEEC. These results indicate that the proposed protocol is suitable for long-term sensing applications where stable operation and extended network lifetime are important.

Future work can extend this protocol in several directions. The current study assumes that all sensor nodes have equal energy and remain fixed after deployment, so testing A-QAHR in heterogeneous networks and mobile scenarios would make it more practical. The protocol can also be improved to support applications that need low delay and high reliability, such as industrial monitoring and healthcare IoT systems. Another useful extension is adding security measures to handle faulty or compromised nodes without increasing the energy cost too much. Finally, implementing the protocol on real sensor devices and testing it in real environments would help confirm its performance under practical wireless conditions.

Funding: The authors declare that no specific funding was received for this work.

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