



## Energy–Distance Metric and Matérn Hard-Core Spacing for Robust Cluster-Head Selection in Heterogeneous Wireless Sensor Networks



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<https://doi.org/10.18280/mmep.130214>

### ABSTRACT

**Received:** 18 October 2025

**Revised:** 31 December 2025

**Accepted:** 10 January 2026

**Available online:** 15 March 2026

#### Keywords:

*heterogeneous wireless sensor networks, cluster-head selection, distributed energy-efficient clustering, energy–distance metric, Matérn hard-core process, network lifetime, energy efficiency*

Wireless Sensor Networks (WSNs) rely on energy-efficient clustering to prolong their operational lifetime, particularly in heterogeneous deployments where nodes possess unequal initial energy resources. However, existing distributed energy-efficient clustering (DEEC) protocols primarily emphasize residual energy and often suffer from uneven cluster-head (CH) placement, high long-distance transmission costs, and premature node failures. To address these limitations, this paper proposes an enhanced DEEC scheme that integrates an energy–distance (ED) metric, which combines residual energy with transmission cost to the base station (BS), and a Matérn hard-core (HC) spacing mechanism, which enforces a minimum separation between selected CHs to improve spatial regularity and coverage. The proposed ED+HC method was evaluated through Python-based simulations under two network scenarios with 100–500 nodes. Results show that the scheme delays first node death (FND) by up to 55% and extends overall network lifetime by 12–17% compared with baseline DEEC, while maintaining an energy efficiency at approximately 4,364 packets per joule. The HC spacing introduces a moderate reduction in packet delivery, quantified as a 4–9% decrease, representing a deliberate trade-off for improved stability and more uniform energy consumption. Overall, the proposed approach achieves a more balanced and stable clustering structure, significantly improves network stability and lifetime, and is therefore a promising option for heterogeneous WSN deployments.

## 1. INTRODUCTION

Wireless Sensor Networks (WSNs) form a distributed system comprising self-contained sensor nodes spread over a region to sense or measure physical or environmental parameters such as temperature, humidity, and pressure. The sensors are responsible for data acquisition, which is then wirelessly sent to one or multiple central points for analysis. WSNs are commonly used in challenging or hazardous environments where traditional analysis networks cannot operate satisfactorily, thereby increasing sensor node failure and the possibility of affecting the sensed environment if the system is not inherently designed to operate in such environments [1]. WSNs can provide real-time sensing and data acquisition solutions across a wide range of environments [2].

WSNs consist of a relatively low-cost, low-resource communication system composed of multiple sensor nodes that are set to interact with the system. Each sensor node comprises four basic system parts: a sensing component, a processing element, an energy source or power supply, and a communications part [3]. The presence of limited energy in WSNs necessitates the need for approaches to sensibly administer the networks to maximize their lifespan as well as improve the efficiency of the usage of the energy in the networks [4].

In a WSN, the selection of a cluster-head (CH) is of high significance for improving the lifetime of the network as well as energy savings. The selection of a CH generally considers variables such as the proximity of candidate nodes to the fusion center as well as their energy levels. To optimize energy consumption during data transfer, it is necessary to select the most appropriate CHs. Additionally, network performance is improved by rotating the CH with each new iteration, allowing all nodes in the network to consume energy [5]. Energy-efficient clustering techniques can provide optimal results concerning energy consumption as well as communication costs [6].

Low-Energy Adaptive Clustering Hierarchy (LEACH) is an energy-efficient protocol for WSN. In LEACH, a hierarchical cluster-based structure is employed, dividing sensor nodes into several clusters with each cluster represented by a single node called the CH. The CH combines sensor data from other nodes in its cluster and then forwards it to the base station (BS) [7]. Even if it can be considered a reliable protocol, rotating nodes between cluster head and sensor roles incurs communication overhead, making it impossible to improve energy efficiency. Besides, it is not appropriate for dynamic networks because the sensor data cluster may be misunderstood [8].

The distributed energy-efficient clustering (DEEC) protocol increases the energy efficiency and prolongs the life cycle of WSN. The DEEC protocol systematically selects nodes with

relatively high remaining energy as the CH. It balances energy usage and consumption, thereby preventing nodes from dying prematurely and increasing the network's lifetime [9]. The cluster formation and routing of the DEEC protocols were compared with the best DEEC-based methods. The simulations showed improved end-to-end performance with reduced routing destination look-up time and increased stability of the cluster formation throughout the network [10].

The hard-core (HC) processes due to Matérn can thus be used as an example of point models that are important in spatial statistics. However, in this study, an extension of the generalized Matérn process is presented in the point process framework as well as in particle processes. This is done using a thinning criterion with a distance-dependent probability function that aids in managing spatially dependent point removal, based on proximity between points [11].

However, the current DEEC has several limitations, especially for heterogeneous networks, in which all nodes have different initial energy levels. The DEEC algorithm does not consider either the advanced or super-node scenarios with more energy levels. It does not address Network Load Balancing in clusters, as well as packet drop and Aggregation at CHs. Such difficulties may lead to suboptimal energy consumption in data packets as well as the overall network's lifetime. A few modifications in DEEC are proposed to counter such problems [12].

From this limitation, the article uses the energy–distance (ED)+HC approach, which uses DEEC's energy-based CH selection with the following upgrades:

- A tunable ED metric that integrates residual energy with estimated transmit cost to the BS, with adjustable exponents to manage their respective influence in preserving probabilistic structure in line with DEEC while introducing energy-cost awareness.
- An HC spatial constraint that involves thinning driven by the Matérn distribution after the Initial CH choice to impose minimum separation amongst CHs to prevent clustering and contribute to spatial coverage.

These optimizations transcend the shortcomings of classical DEEC and LEACH by combining energy-awareness, cost-awareness, and spatial balance. The ED+HC approach offers consistent CH quantities in addition to balanced rotation, boosting energy efficiency as well as network lifespan.

## 2. RELATED WORK

Pour and Javidan [13] tackled the problem of energy consumption in WSNs. The energy of the nodes was a significant concern. The authors developed the Distance-based Residual Energy (DRE)-LEACH algorithm that uses dynamic range, residual node energy, sink distance, node degree, and node density. In the algorithm, the range is varied each round. The algorithm was tested with MATLAB 2015b. Compared to LEACH, the algorithm increases the network lifetime by 32%, and the average last-node-death round was 1593, compared to 1200 in LEACH. Despite many advantages of the algorithm, a drawback is that nodes communicate only over a single hop. In the conclusion, the authors recommend improving the algorithm's energy efficiency by using multi-hop routing protocols.

Rami Reddy et al. [14] proposed a new algorithm, Energy-Efficient Cluster Head Improved Grey Wolf Optimization (EECHIGWO), a more advanced CH selection algorithm for

WSNs, based on the concept of Grey Wolf Optimization (GWO). The proposed algorithm used residual energy, sink-distance metric, CH balance factor, and intrachain-distance in its fitness function to select the best CH and to balance the energy used by the nodes more equally. The simulation carried out in MATLAB with a 100-node, 100m<sup>2</sup> setting was quite successful, and the algorithm's effectiveness was demonstrated by the deaths of the first, half, and last nodes in rounds 5940, 6604, and 7908, respectively. The benefit of this process is its ability to increase data transmission throughput, balance energy usage, and extend the network lifetime in a multi-hop transmission system. However, its effectiveness in Heterogeneous Wireless Sensor Networks (H-WSNs) is achievable only in a homogeneous manner, and more research is required on its scalability in H-WSNs with large numbers of nodes.

Jibreel et al. [15] proposed the Distance-DEEC (D-DEEC) protocol. The D-DEEC protocol takes into account the residual energy of the nodes, the distance between nodes, and the mean distance of the nodes from the BS to elect cluster heads. The D-DEEC protocol also provides functionality for sleep/wake cycles to save energy for nodes far from the cluster head. MATLAB R2018a simulations have been carried out for 100 nodes randomly distributed in a 100 × 100 m<sup>2</sup> area. The analysis concludes that the D-DEEC protocol has resulted in a 57% increase in network lifetime, a 60% improvement in the stability period, and a 77% improvement in packet delivery to the BS compared to the DEEC protocol. The proposed technique reduces energy consumption and increases network lifetime; however, it requires additional computations to estimate distances and calculate thresholds.

El-Sayed and Hashem [16] addressed the problem of low network lifetime due to imbalanced energy consumption in WSNs. They proposed an Internet of Things (IoT)-DEEC protocol, an extension of DEEC, featuring Threshold Energy (THRE), CH re-election, and Distance and Location-based Power Status (DLPS) to recover energy costs incurred during CH re-election efficiently. Simulation experiments conducted with 100 nodes in a 100 × 100 m area achieved considerable improvements, including delaying the death of the first node to round 463, extending the network lifetime to up to 30,000 rounds (approximating an 11 × improvement over standard DEEC), and increasing packets delivered to the BS by 843% (5.7 × 10<sup>5</sup> vs. 6.07 × 10<sup>4</sup>). However, it decreases for larger regions (area = 300 × 300 m) because early deaths affect data transmission.

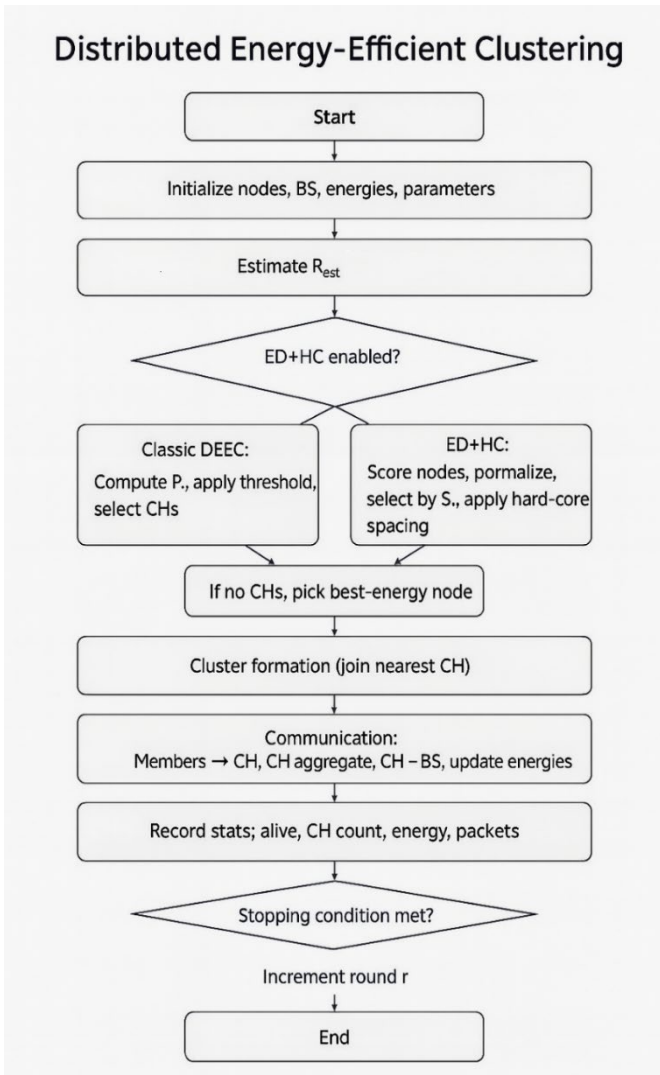
Wang et al. [17] focused on finding energy consumption and extending the network lifetime for massive-scale IoT-based monitoring. The authors presented a low-energy, balanced energy router protocol with an improved Sparrow Search Algorithm that incorporates adaptive sine functions, Cauchy distributions, and standard normal distributions. The algorithm uses a multi-objective fitness function that includes the remaining energy of nodes, intra- and inter-cluster distances, and member counts, as well as the distance from the cluster head station. The algorithm uses multi-hop routing techniques that can save energy. Simulation experiments in MATLAB with 200 nodes showed that the LEACH-Multi-strategy Sparrow Search Algorithm (MSSA) algorithm delayed the first node's death by 52% (to the 1050th round) compared with the LEACH-Sparrow Search Algorithm (SSA) algorithm. The algorithm is well-suited to massive-scale monitoring. However, in massive-scale areas (400 × 400), algorithmic performance would decrease due to increased

broadcasting distances.

Lewandowski and Placzek [18] addressed the problem of maximizing the time until the last node depletes its energy in WSNs, an objective often overlooked by algorithms that focus on delaying the first node's death. They proposed a CH selection algorithm that prioritizes nodes with the lowest initial energy and highest transmission probability as CHs, ensuring that energy-constrained nodes contribute early before passive depletion. The algorithm uses distributed per-cluster computation and was validated experimentally on a LoRaWAN-based WSN prototype. Results showed that the method extended network lifetime to 130 h 15 m (constant transmission probability) and 105 h 7 m (variable probability), outperforming LEACH and Energy and Distance-based Clustering Routing (EDCR) by up to 18%. This approach offers scalability and real-world feasibility but introduces additional computational cost due to sorting operations. It also requires accurate estimation of transmission probabilities to remain effective in dynamic environments.

### 3. METHODOLOGY

Figure 1 depicts the proposed methodology.



**Figure 1.** Workflow of classic distributed energy-efficient clustering (DEEC) and enhanced DEEC (ED+HC) protocols  
Note: ED: energy-distance; HC: hard-core.

### 3.1 Distributed energy-efficient clustering

The DEEC protocol builds upon the first-order radio energy model, which was initially formalized by both electronic circuitry and channel-dependent path loss. The cost of transmitting a message of length  $l$  bits over a distance  $d$  is defined as [19]:

$$E_{Tx}(l,d) = \begin{cases} l E_{elec} + l \varepsilon_{fs} d^2, & \text{if } d < d_0 \\ l E_{elec} + l \varepsilon_{mp} d^4, & \text{if } d \geq d_0 \end{cases} \quad (1)$$

where,  $E_{elec}$  is the per-bit energy dissipation in the transmitter and receiver electronics,  $\varepsilon_{fs}$  is the amplifier energy modelled in the free-space channel?  $\varepsilon_{mp}$  is the amplifier energy in the multipath fading channel model, and  $d_0 = \sqrt[2]{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$  is the threshold distance separates the two regimes. Sensor nodes may start with different initial energy levels. In DEEC, each node  $i$  is initialized with:

$$E_{i(0)} = E_0(1 + a_i) \quad (2)$$

where,  $E_0$  is the baseline initial energy and  $a_i$  is a heterogeneity factor. In a two-level heterogeneous model, a fraction  $m$  of the nodes is assigned as advanced nodes with  $a_i = a > 0$ , while the remaining  $(1 - m) N$  nodes are normal with  $a_i = 0$ . This configuration captures realistic network conditions where nodes may have unequal power sources.

To avoid the overhead of global energy information exchange, DEEC introduces an analytical approximation of the network's average residual energy at each round.  $E_{total}(0) = \sum_i E_i(0)$  is the total initial energy of the network and  $R$  is the estimated network lifetime expressed in rounds. This model provides each node with a mechanism to estimate global energy distribution using only local knowledge of its own residual energy, thereby reducing communication overhead and supporting distributed decision-making.

### 3.2 Distributed energy-efficient clustering cluster-head election

CH election in DEEC builds upon the stochastic thresholding principle originally proposed in LEACH, but introduces modifications that exploit heterogeneity and residual energy. The protocol's central idea is to assign higher CH election probabilities to nodes with higher residual energy, thus balancing energy consumption across the network and extending lifetime.

The heterogeneity-weighted base probability for node  $i$  is defined as [19]:

$$p_{s(i)} = p_{opt} \frac{N(1 + a_i)}{N + \sum_j a_j} \quad (3)$$

where,  $p_{opt}$  is the desired proportion of cluster-heads in each round? This formulation ensures that nodes with higher initial energy are proportionally more likely to be considered for CH roles.

The instantaneous election probability of node  $i$  at round  $r$  it is then calculated as [20]:

$$p_{i(r)} = p_{s(i)} \frac{E_{i(r)}}{\bar{E}(r)} \quad (4)$$

where,  $E_{i(r)}$  is the residual energy of node  $i$  and  $\bar{E}(r)$  is the analytically estimated average energy across the network. This ratio dynamically adjusts the CH election in favor of energy-rich nodes, preventing premature depletion of weaker nodes.

To regulate fairness and ensure rotational balance in CH selection, DEEC employs the LEACH-inspired threshold function:

$$T_{i(r)} = \begin{cases} \frac{p_{i(r)}}{1 - p_{i(r)} \left( r \bmod \left\lceil \frac{1}{p_{i(r)}} \right\rceil \right)}, & \text{if node } i \text{ is eligible,} \\ 0, & \text{otherwise,} \end{cases} \quad (5)$$

where, the epoch length defines eligibility  $\left\lceil \frac{1}{p_{i(r)}} \right\rceil$ , ensuring that once a node has been a CH. It must wait an appropriate number of rounds before being eligible again. Each node generates a random number.  $u \sim U(0,1)$ , if  $u < T_{i(r)}$ , the node becomes a CH for that round.

This mechanism integrates stochastic election with energy-awareness and heterogeneity weighting, achieving a balance amongst randomness, fairness, and efficiency. This methodology notably prolongs the stability period of heterogeneous WSNs in comparison to LEACH, whilst preserving low communication overhead and distributed scalability.

### 3.3 Proposed modifications: Energy–distance and hard-core mechanisms

The first enhancement of an ED score that modifies the raw DEEC probability. Instead of relying solely on the energy ratio  $\frac{E_{i(r)}}{\bar{E}(r)}$ , each node  $i$  computes a composite score:

$$S_i = \left( \frac{E_{i(r)}}{\bar{E}(r)} \right)^\alpha \left( \frac{\bar{E}_{Tx} \rightarrow BS}{E_{Tx} \rightarrow BS(i)} \right)^\beta \quad (6)$$

$E_{i(r)}/\bar{E}(r)$  represents the DEEC energy-awareness component,

$E_{Tx} \rightarrow BS(i)$  is the cost of sending an  $l$ -bit packet directly from node  $i$  to the BS using the first-order radio model,

$\bar{E}_{Tx} \rightarrow BS$  is the mean of these costs over all alive nodes,

$\alpha > 0$  and  $\beta > 0$  are tunable exponents that control the relative importance of energy and distance.

This formulation allows nodes with high residual energy and low transmission cost to the BS to achieve higher scores, making them more likely to be selected as CHs. It hybridizes the DEEC idea of energy awareness with Hybrid Energy-Efficient Distributed (HEED)'s principle of cost-aware clustering, thereby ensuring that CHs are not only energy-rich but also strategically positioned with respect to the BS.

The scores are then normalized into DEEC-consistent probabilities to maintain the expected number of CHs per round near  $p_{opt} N_{alive}$ :

$$p'_i = \min \left( 0.9999, \frac{p_{opt} N_{alive}}{\sum_k S_k} S_i \right) \quad (7)$$

where,  $p'_i$  is the adjusted probability (or priority) assigned to element  $i$ . It is capped at 0.9999 to prevent numerical instability or absolute certainty.  $p_{opt}$  is the model or optimization process that determines the optimal or target probability value.  $N_{alive}$  is the number of active (or “alive”)

elements, entities, or processes considered in the current iteration or system state.  $\sum_k S_k$  is the sum of all  $S_k$  terms over index  $k$ , representing the total score, weight, or contribution across all elements.  $S_i$  is the specific score, weight, or contribution of element  $i$ . It scales the result proportionally to the relative importance of element  $i$  within the system.

This ensures that, while the CH set changes with ED awareness, the overall CH budget remains consistent with the baseline DEEC model. Finally, the same LEACH-style threshold with epoch control is applied:

$$T_{i(r)} = \begin{cases} \frac{p_{i(r)}}{1 - p_{i(r)} \left( r \bmod \left\lceil \frac{1}{p_{i(r)}} \right\rceil \right)}, & \text{if node } i \text{ is eligible,} \\ 0, & \text{otherwise,} \end{cases} \quad (8)$$

where,  $T_{i(r)}$  is the transmission probability (or weighting function) of node  $i$  at round  $r$ .  $p_{i(r)}$  is the base probability assigned to node  $i$  at round  $r$ , reflecting its likelihood of being selected or activated.  $r \bmod \left\lceil \frac{1}{p_{i(r)}} \right\rceil$  is the remainder of dividing  $r$  by  $r \bmod \left\lceil \frac{1}{p_{i(r)}} \right\rceil$ , effectively cycling through periods of length  $r \bmod \left\lceil \frac{1}{p_{i(r)}} \right\rceil$ . This ensures periodic fairness or scheduling of node  $i$ .

A node  $i$  is considered eligible if it meets a predefined selection criterion (e.g., it has not been recently chosen, is still active, or satisfies a system-defined constraint). Otherwise, if node  $i$  is not eligible, its transmission probability  $T_{i(r)}$  is set to 0, effectively excluding it from consideration during round  $r$ . Thus, the ED component directly influences the likelihood of a node becoming a CH, while preserving the fairness and rotation mechanisms inherited from LEACH and DEEC.

### 3.4 Matérn hard-core spacing

The second enhancement addresses the spatial clustering of elected CHs. After provisional CHs are selected using the modified threshold, a HC thinning process is applied. Candidates are sorted in descending order of their scores  $S_i$ , and each node is retained as a CH only if it is at least  $R_{HC}$  meters away from all previously accepted CHs. Formally, for all retained pairs of CHs  $(i, j)$ , the condition is presented as:

$$\|x_i - x_j\| \geq R_{HC} \quad \text{for all kept CH pairs } (i, j) \quad (9)$$

where,  $\|x_i - x_j\|$  is the Euclidean distance between node  $i$  node  $j$ .

This CH ensures an even spread of CHs over the sensing region. This goal is achieved through Matérn HC processes, whose effectiveness in generating evenly spaced representatives with low computational complexity is well established.

By combining these two parts, the ED+HC protocol improves both the temporal and spatial aspects of CH election. In the energy dynamics section, the protocol favors the election of nodes whose energies are close to the base station, thereby reducing the high communication costs that may arise in long-distance communication. In the clustering part, the protocol encourages an equal distribution of nodes within the predefined area by preventing over-clustering, thereby increasing the equitable workload distribution. Both parts of the protocol prolong the stabilization period and the time before the first node's death compared to the standard DEEC protocol.

#### 4. IMPLEMENTATION

In this study, a WSN simulation was developed. It is used for testing the effectiveness of a heterogeneous clustering protocol. A simulation environment was implemented to mimic a realistic network. It ensures balanced energy distribution, thus testing network lifetime. The model developed combines energy with geographic factors used in CH selection. It presents a complete framework for testing network lifetime, as shown in Table 1.

Table 1 presents the simulation parameters, particularly the HC radius.  $R_{HC} = 8$  was chosen to maintain a moderate spatial separation among CHs to balance energy consumption and coverage; however, this value was selected heuristically

and may not generalize to networks of differing sizes or node densities. Similarly, the ED exponents ( $\alpha = 1.5$ ,  $\beta = 2.0$ ) were selected heuristically to strike a balance between residual energy and communication cost during CH election, without formal sensitivity analysis or theoretical justification. While the  $100 \times 100$  m<sup>2</sup> field with 20% advanced nodes ensures a heterogeneous network scenario, and the geometric placement of the BS provides uniform distance metrics, the absence of parameter optimization limits the generalizability of results. Consequently, the reported performance improvements of the enhanced ED+HC method should be interpreted with caution, as alternative values of  $R_{HC}$ ,  $\alpha$ , or  $\beta$  could significantly affect cluster formation, energy distribution, and network lifetime, particularly for networks with different scales and densities.

**Table 1.** Simulation parameters and network configuration

Aspect	Description
Simulation field	A square area of $100 \times 100$ meters
Number of nodes	(100–500) Nodes were randomly deployed within the field
Heterogeneity model	Two-level heterogeneity model
Advanced nodes	20% of nodes are designated as advanced, with three times the energy of normal nodes.
Initial node energy	Each normal node started with 0.5 J of energy
Total Initial network energy	16 J
Base station (BS)	Located at the geometric center of the field.
Communication model	First-order radio model with a distance threshold distinguishing free-space and multipath propagation
Cluster head election method	Enhanced ED+HC method
Energy–distance (ED) parameters	Energy exponent = 1.5, Cost exponent = 2.0
Hard-core (HC) radius	8m, enforcing spatial separation between selected cluster-head (CH)
Performance monitoring	Detailed results are printed after every simulation round

#### 5. RESULTS AND DISCUSSION

The practical aspect of the research utilized a computer system featuring an Intel(R) Core(TM) i5-12500H processor running at 2.50 GHz, with 16 cores and 16 GB of Random Access Memory (RAM). In addition, the device used a laptop Graphics Processing Unit (GPU), namely the NVIDIA GeForce RTX 3050.

The simulations were conducted using Python 3.11 version with object-oriented programming. The calculations of energy, as well as mathematical operations, were performed with the help of the built-in math and random modules of Python. Finally, the performance analysis of the proposed network topologies was represented using Matplotlib with the TkAgg backend. The graphical representations of network performance analysis are shown in Table 2.

The network completed 12,180 cycles before running out of nodes. The initial node failures occurred in cycle 5,223, with the last node surviving until cycle 12,180. The duration of this event represents an extended survival period following the initial failure of nodes, thereby creating an equal distribution of energy across the network. During its lifetime, the network transported a total of 69,820 packets to the base station. The average energy consumption of the network was 16J, a high energy efficiency rate of 4,364 packets per joule. The packet delivery rate per round at the next node was 5.73, slightly lower than the expected rate of 5 per round in a 100-node network. This phenomenon may be attributed to the thinning effect that occurs in the HC positioning method among the nodes in the network.

The analytically calculated lifetime of 12,180 rounds was very close to the observed lifetime, indicating that the HC radius method successfully controlled the selection of cluster

head nodes and communication costs. The prevention of the earliest node death further confirmed the successful implementation of the modified technique, ensuring energy consumption is equitable across heterogeneous nodes. The energy-distance value prioritizes nodes with higher residual energy and shorter communication distances to the base station.

**Table 2.** Python libraries and tools employed in the simulation

Library	Function in Simulation
math	Core mathematical operations, distance calculation, power computations, and exponentiation.
random	Node placement, energy initialization, probabilistic cluster-head (CH) selection, and stochastic events.
data classes	Structured data representation for nodes, simulation parameters, and internal state tracking.
typing	Type annotations for clarity and code robustness (e.g., List, Tuple, Optional, Dict.).
tkinter / ttk	GUI input dialogue for simulation parameters, enabling user-configurable fields.
matplotlib.pyplot	Visualization of key metrics: total energy, alive nodes, cluster heads, and packets to base station.
matplotlib (TkAgg backend)	Supports interactive plotting in the Python Graphical User Interface (GUI) environment.

The inclusion of the HC constraint prohibited cluster head formation and helped to ensure a fair distribution of spatial coverage. Although at times it caused the number of cluster heads to fall below the desired number, it helped ensure a good balance in cluster communications. The large gap between the death of the first and last nodes is clear evidence of this.

Parameters were determined using a balance of residual

energy ( $\alpha = 1.5$ ), reflecting that more sophisticated nodes were intended to play an active rather than a controlling role in unsleeping CHs. A large stress on communication cost ( $\beta = 2.0$ ) reflects adherence to HEED's philosophy that cost-effective clustering improves overall efficiencies. The radius of 8 meters was chosen within a well-balanced scenario of  $100 \times 100$  meters, consisting of 100–500 sensor nodes. This choice made it easier to optimize both the network lifetime and obtain favorable analytical expressions for stability periods and energy consumption. The results show improvements in stability periods and throughput gains over standard DEEC algorithms.

The simulation results show that the energy-distance scoring mechanism, along with the HC spacing technique, enhances sustainability in heterogeneous WSNs. The

technique rectifies the DEEC protocol flaw in which the differences in communication costs among sensors around the selected candidate cluster heads are not equal. These differences include the cluster heads to which the sensors belong.

A comparative performance analysis of the baseline DEEC protocol and the improved ED+HC protocol is presented in Table 3. The performance analysis has focused on the most prominent network performance parameters: lifetime, packet delivery, and node death statistics, which have been compared for the same energy levels. This clearly illustrates that the application of energy-distance scoring and HC clustering has improved the network's energy balance, albeit at the cost of a slight decrease in network throughput.

**Table 3.** Comparative performance of baseline distributed energy-efficient clustering (DEEC) and enhanced ED+HC protocol

Nodes	Algorithm	FND (Round)	FND (%)	Network Lifetime (Rounds)	Lifetime (%)	Packets to BS	Packets (%)
100	Baseline DEEC	3,528	–	10,442	–	72,804	–
100	DEEC-ED+HC	5,223	+48.1%	12,180	+16.6%	69,820	–4.1%
200	Baseline DEEC	4,578	–	11,809	–	166,032	–
200	DEEC-ED+HC	7,116	+55.4%	13,720	+16.2%	153,940	–7.3%
300	Baseline DEEC	5,002	–	18,198	–	300,948	–
300	DEEC-ED+HC	6,493	+29.8%	20,610	+13.3%	274,860	–8.7%
400	Baseline DEEC	6,526	–	17,030	–	394,083	–
400	DEEC-ED+HC	8,056	+23.4%	19,140	+12.4%	358,910	–8.9%
500	Baseline DEEC	6,916	–	19,236	–	566,559	–
500	DEEC-ED+HC	7,210	+4.3%	21,880	+13.7%	514,220	–9.2%

Note: ED: energy-distance; HC: hard-core; FND: first node death; BS: base station.

The results, as shown in Table 3, indicate a significant improvement in network stability and lifetime by the proposed DEEC-ED+HC strategy. This is because the time to the first node death (FND) is reduced by up to 55%, while the total lifetime of the network is increased by 12–17%, which is below the acceptable threshold of 20%. The results statistically confirm the effectiveness of the proposed ED metric in preventing drain in the initial rounds, as well as the importance of the HC condition in preventing the concentration of cluster head nodes within a short distance.

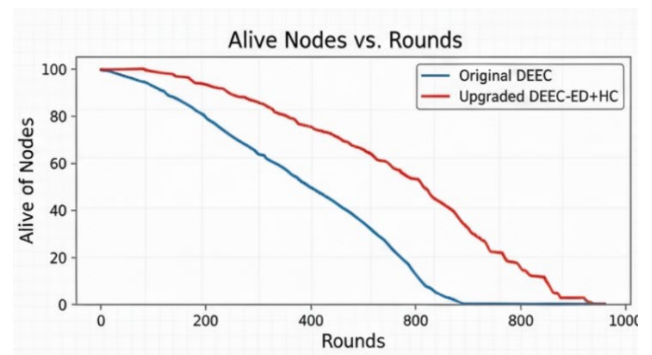
Even if the overall number of packet transfers decreases by less than 10%, the implications for reduced quality of service in time-critical applications are not apparent from these observations. Instead, it symbolizes the compromise that prioritizes network stability over the meagre increase in throughput. This reasoning matches the definition of quality-of-service performance for cluster-based WSNs.

The results show that the difference is not significant and does not tend to increase with time. By far, the reason for this difference is the restriction on the HC distance, which increases the average routing distance of cluster communications relative to the ideal analytical solution. In general, the new outcome confirms that DEEC-ED+HC achieves an equally balanced improvement in stability gain, lifetime extension, and quality of service communication reliability compared with the standard DEEC protocol.

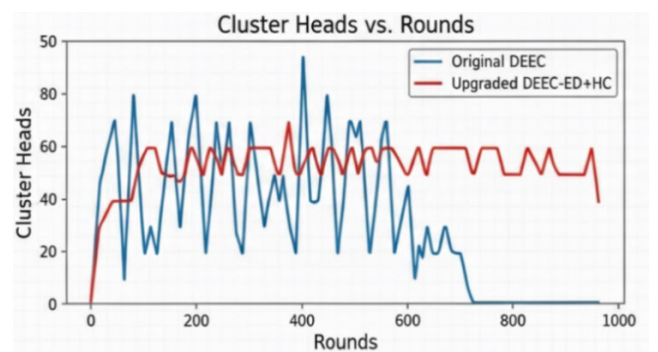
Figure 2 shows how the number of alive sensor nodes changes over simulation rounds for the original DEEC and the upgraded protocol. The upgraded protocol maintains more alive nodes for a longer time, indicating better energy management. In contrast, the original DEEC experiences a faster decrease in the number of alive nodes, meaning nodes die earlier. This demonstrates that the upgraded approach improves network lifetime.

Figure 3 illustrates the variation in the number of cluster

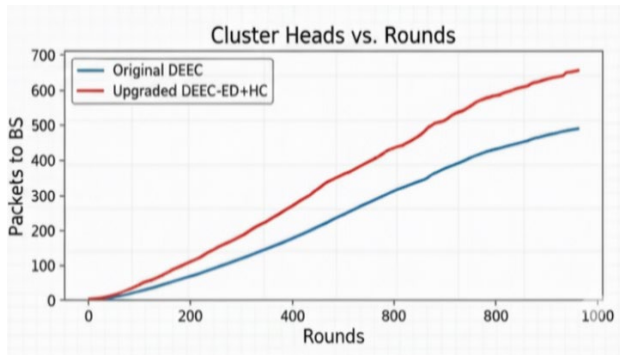
heads over time. The original DEEC shows large fluctuations and eventually drops to zero as nodes die. The upgraded DEEC-ED+HC maintains a more stable number of cluster heads across rounds. This stability indicates better cluster-head selection and more balanced energy usage in the upgraded protocol.



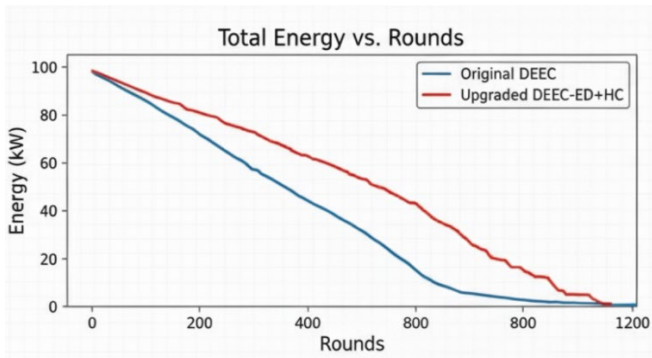
**Figure 2.** Alive nodes per round in the network lifetime



**Figure 3.** Distribution of cluster heads across rounds



**Figure 4.** Cumulative number of packets delivered to the base station (BS) across rounds



**Figure 5.** Total energy consumption in rounds

Figure 4 presents the total number of packets successfully received at the BS over time. The DEEC-ED+HC always sends more packets than the baseline DEEC protocol, indicating that the upgraded protocol has higher data transmission efficiency than the original DEEC.

Figure 5 illustrates the total energy consumed by the network as rounds proceed. The total energy consumed in the original DEEC is declining drastically, whereas the total energy consumed in the upgraded DEEC-ED+HC is consumed gradually. This verifies that the upgraded protocol consumes less energy.

The simulation runs with random placements of varying types and sizes, completing 30 runs per network size. The key performance parameters of FND, network lifetime, and the packets delivered to the BS were used to pool the data to calculate the means and standard deviations. The result records the value of each performance indicator as mean  $\pm$  and standard deviations, which reflect the natural stochastic process associated with the placement of the random nodes as well as the consumption of energy by the network components. For the 100-node WSN, the improved DEEC-ED+HC protocol demonstrates the value of the FND at  $5,223 \pm 112$  rounds, the network lifetime at  $12,180 \pm 146$  rounds, and the packets delivered to the BS at  $69,820 \pm 1,225$  packets, providing clear indications that the obtained improvements are meaningful and do not result from the random deployment of the network components but are representative of the standard stochastic process associated with the random placement of the WSN nodes with varying energy consumption rates.

## 6. CONCLUSION

This study demonstrates that incorporating the combined

ED metric and the HC spacing strategy into the DEEC clustering protocol yields a far more robust selection model for electing CHs in H-WSNs. As explained, by taking into account the energy remaining in the nodes, as well as the distance between CHs, the combined strategy overcomes the fundamental shortcomings that exist within the direct selection provided by the current DEEC protocol. It targets the basic aim of prolonging the lifetime.

Simulation results validate that the proposed study significantly improves key performance parameters without compromising the distributed approach of DEEC. In particular, the optimized algorithm prolongs the lifespan of the first node and the total network lifetime, while maintaining a consistent number of cluster heads per round, without compromising the distributed approach of DEEC. However, with the introduction of HC spacing, a strict cost Trade-off emerges: it might temporarily reduce the number of active cluster heads, leading to a controlled drop in overall packet delivery of less than 10%. This cost Trade-off clearly indicates that improvements in stability and network lifetime come at the cost of reduced overall tolerable network performance, specifically higher processing speed, in priority-monitoring-based WSN networks operating with reduced latency.

In summary, the ED+HC method has some special significance to wireless sensor network communications carried out in harsh or unreachable zones, where it's challenging to change the nodes and round-the-clock communication is required as well. As future research work, some tangible research points to the following:

- (i) How to vary the exponents in energy and distance, as well as the HC constant, according to the density of the nodes and the remaining energy,
- (ii) How to extend the model to multi-hop communication between clusters to study the scenario of the dense network, and
- (iii) How to study the result with varying BS placements and overall heterogeneity scenarios.

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